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Edited Book

How to cite:

Kravcik, Milos; Mikroyannidis, Alexander; Pammer, Viktoria; Prilla, Michael and Ullmann, Thomas eds. (2016). Proceedings of the 6th Workshop on Awareness and Reflection in Technology Enhanced Learning. In conjunction with the 11th European Conference on Technology Enhanced Learning: Adaptive and Adaptable Learning. CEUR Workshop Proceedings, 1736. CEUR.

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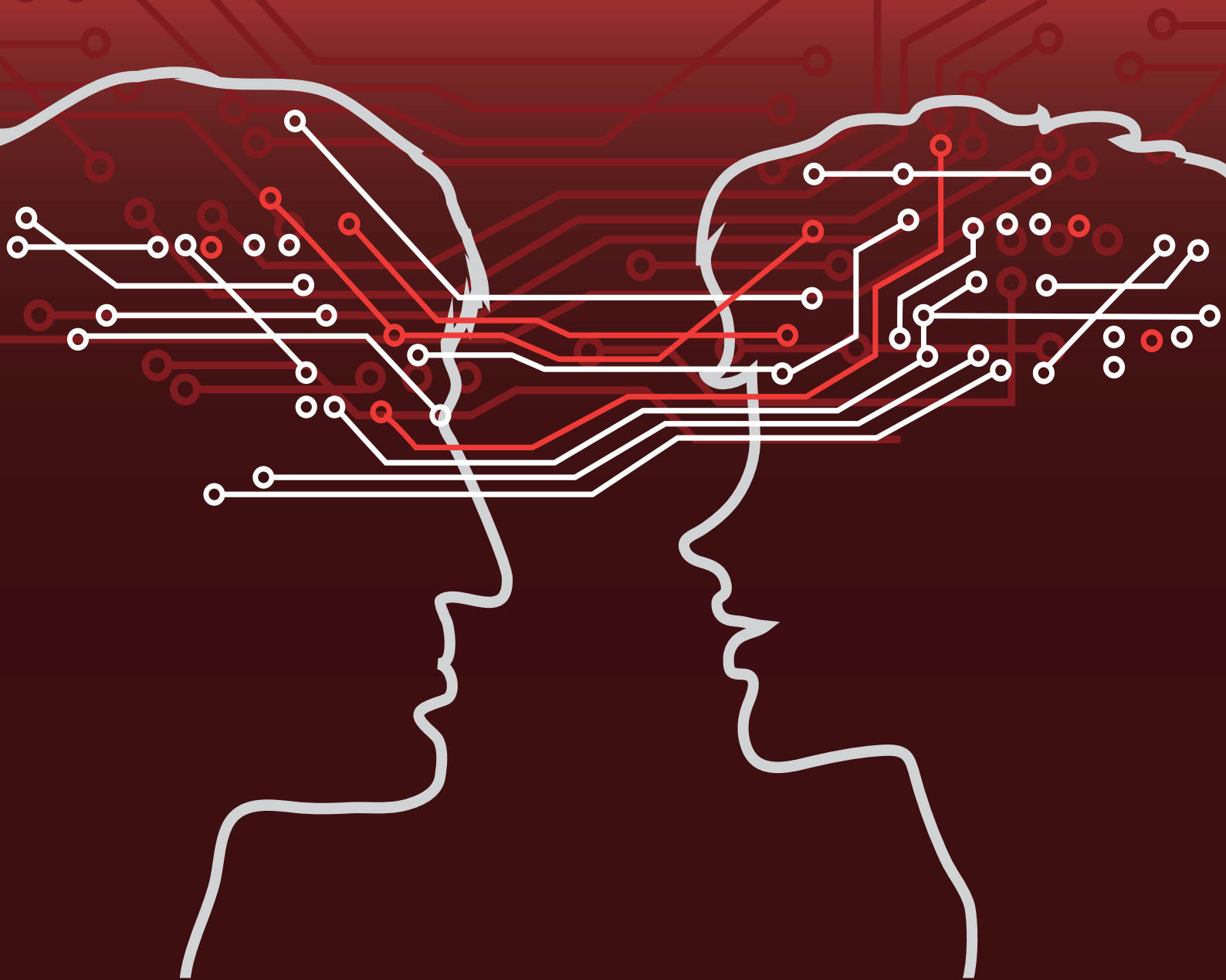
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Version: Version of Record

Link(s) to article on publisher's website:
<http://ceur-ws.org/Vol-1736/>

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Proceedings of the 6th Workshop on Awareness and Reflection in Technology Enhanced Learning

**In conjunction with the 11th European Conference on Technology
Enhanced Learning: Adaptive and Adaptable Learning**

Lyon, France, September 13, 2016

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Please refer to these proceedings as

Milos Kravcik, Alexander Mikroyannidis, Viktoria Pammer, Michael Prilla, Thomas Ullmann (Eds.): Proceedings of the 6th Workshop on Awareness and Reflection in Technology Enhanced Learning. In conjunction with the 11th European Conference on Technology Enhanced Learning: Adaptive and Adaptable Learning. Lyon, France, September 13, 2016. Available online at <http://ceur-ws.org/>.

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The front-cover was created by Harriett Cornish (The Open University, KMi).

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Learning Analytics for Awareness and Reflection

Awareness and reflection are viewed differently across the disciplines informing Technology-Enhanced Learning (CSCW, psychology, educational sciences, computer science and others). The ARTEL workshop series brings together researchers and professionals from different backgrounds to provide a forum for discussing the multi-faceted area of awareness and reflection. 2016 was the 6th workshop in this series.

Through the last ARTEL workshops at EC-TEL the topic has gained maturity and questions addresses are converging towards the usage of awareness and reflection in practice, its implementation in modern organisations, its impact on learners and questions of feasibility and sustainability for awareness and reflection in education and work. To reflect the growing maturity of research in ARTEL over the years in conjunction with the latest trends in TEL, this year's topic particularly invited contributions that deal with the contribution and impact of Learning Analytics on awareness and reflection. The motto of the workshop this year was:

'Learning Analytics for Awareness and Reflection: How can Learning Analytics methodologies and tools support awareness and reflection in different learning contexts?'

Summary of the contributions

The #ARTEL16 workshop accepted two full papers, and four short papers. The accepted papers discuss awareness and reflection according to three themes.

Three papers focused on the theme learning analytics, visualisation and dashboards for awareness and reflection.

The full paper 'Designing Generic Visualisations for Activity Log Data' written by Granit Luzhnica, Angela Fessler, Eduardo Veas, Belgin Mutlu, and Viktoria Pammer aims at an important issue in lifelong and professional learning that is how to visualize log data from various resources in a generic way without knowing in advance concrete analytic tasks. The authors have implemented a tool, called Vis-Tool. The presented evaluation compares Vis-Tool with three specific applications, considering ten evaluation tasks. The results show possible benefits of Vis-Tool.

The short paper 'Reflection Analytics in Online Communities: Guiding Users to become active in Collaborative Reflection' of Oliver Blunk, Michael Prilla, and Graham Attwell describes a prototype visualisation that aims at supporting the awareness of students about group activity in the context of reflective online group collaborative work.

The short paper 'Visualizing Online (Social) Learning Processes - Designing a Dashboard to Support Reflection' co-authored by Darya Hayit, Tobias Hölterhof, Martin Rehm, Oskar Carl, and Michael Kerres provides an overview of a prototype dashboard for visualising social learning processes.

Two papers were accepted that provide a perspective on collaborative/social reflection and reflection in the workplace.

The short paper 'E-portfolio for Awareness and Reflection in a Blended Learning Environment' written by Morin Roa, Eliana Scheihing, Julio Daniel Guerra, and Carlos Blaña presents research about an e-portfolio used for awareness and reflection within a blended learning community. The e-portfolio has been evaluated by members of this community in terms of its usability and usefulness.

Tracie Farrell Frey, George Gkotsis, and Alexander Mikroyannidis present in their short paper 'Are you Thinking what I'm Thinking? Representing Metacognition with Question-based Dialogue' an early prototype and background literature for a tool to create representational artefacts of metacognitive thinking in a collaborative, social environment.

The third theme of the workshops was about literature reviews and theoretical contributions to awareness and reflection.

The short paper 'Considering Self-Efficacy in Reflection' by Birgit Krogstie and John Krogstie discusses the relationship between self-efficacy and reflective learning. The authors argue that as self-efficacy is instrumental in shaping the experiences a person actually generates, and experience is the 'object' of reflective learning, self efficacy needs to be considered in designing the reflection activity.

Awareness and reflection workshop series

The official workshop webpage can be found at <http://teleurope.eu/artel16>

The 6th Workshop on Awareness and Reflection in Technology Enhanced Learning (ARTEL 2016) is part of a successful series of workshops.

- 5th Workshop on Awareness and Reflection in Technology Enhanced Learning (ARTEL15). Workshop homepage: <http://teleurope.eu/artel15>. Proceedings: <http://ceur-ws.org/Vol-1465/>.
- 4th Workshop on Awareness and Reflection in Technology Enhanced Learning (ARTEL14). Workshop homepage: <http://teleurope.eu/artel14>. Proceedings: <http://ceur-ws.org/Vol-1238/>.
- 3rd Workshop on Awareness and Reflection in Technology Enhanced Learning (ARTEL13). Workshop homepage: <http://teleurope.eu/artel13>. Proceedings: <http://ceur-ws.org/Vol-1103/>.
- 2nd Workshop on Awareness and Reflection in Technology Enhanced Learning (ARTEL12). Workshop homepage: <http://www.teleurope.eu/artel12>. Proceedings: <http://ceur-ws.org/Vol-931/>.
- 1st European Workshop on Awareness and Reflection in Learning Networks (ARNets11). Workshop homepage: <http://teleurope.eu/arnets11>. Proceedings: <http://ceur-ws.org/Vol-790/>

- Augmenting the Learning Experience with Collaborative Reflection (ALECR11). Workshop homepage: <http://www.i-maginary.it/ectel2011/index.html>
- 1st Workshop on Awareness and Reflection in Personal Learning Environments (ARPLE11). Workshop homepage: <http://teleurope.eu/arple11>. Proceedings: http://journal.webscience.org/view/events/The_PLE_Conference_2011/paper.html#group_Proceedings_of_the_1st_Workshop_on_Awareness_and_Reflection_in_Personal_Learning_Environments

To stay updated about future events, to share your research, or simple to participate with other researchers, consider joining the group about Awareness and Reflection in Technology Enhanced Learning:

<http://teleurope.eu/artel>

We especially would like to thank the members of the programme committee for their invaluable work in scoping and promoting the workshop and quality assuring the contributions with their peer reviews.

November 2016

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Supporting projects



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Designing Generic Visualisations for Activity Log Data

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Abstract. Especially in lifelong or professional learning, the picture of a continuous learning analytics process emerges. In this process, heterogeneous and changing data source applications provide data relevant to learning, at the same time as questions of learners to data change. This reality challenges designers of analytics tools, as it requires analytics tools to deal with data and analytics tasks that are unknown at application design time. In this paper, we describe a generic visualization tool that addresses these challenges by enabling the visualization of any activity log data. Furthermore, we evaluate how well participants can answer questions about underlying data given such generic versus custom visualizations. Study participants performed better in 5 out of 10 tasks with the generic visualization tool, worse in 1 out of 10 tasks, and without significant difference when compared to the visualizations within the data-source applications in the remaining 4 of 10 tasks. The experiment clearly showcases that overall, generic, standalone visualization tools have the potential to support analytical tasks sufficiently well.

1 Introduction

Reflective learning is invaluable for individuals, teams and institutions to successfully adapt to the ever changing requirements on them and to continuously improve. When reflective learning is data-driven, it comprises two stages: data acquisition and learning analytics. Often, relevant data is data about learner activities, and equally often, relevant activities leave traces not in a single but in multiple information systems. For instance, [14] presents an example where activities relevant for learning about software development might be carried out in svn, wiki and an issue tracking tool. In the context of lifelong user modeling, the learning goals and learning environments change throughout life, different software will be used for learning, while the lifelong (open) user model needs to store and allow analysis across all collected data [12]. Furthermore, as ubiquitous sensing technologies (motion and gestures, eye-tracking, pulse, skin conductivity, etc.) mature and hence are increasingly used in learning settings, the data

sources for such standalone learning analytics tools will include not only information systems but also ubiquitous sensors (see e.g., [24] or [2] who calls this “multimodal learning analytics”). Furthermore, it is frequently the case that concrete data sources, and consequently the questions that users will need to ask of data (analytic tasks) are not a priori known at the time of designing the learning analytics tools. In the context of lifelong learning for instance, at the time of designing a visualization tool, it cannot be foreseen what kind of software will be used in the future by the learner. In the context of the current trend towards rather smaller learning systems (apps instead of learning management systems) it is plausible to assume that learners may wish to exchange the used software regularly (and be it only that they switch from Evernote to another note-taking tool). At the extreme end of generic analytics tools are of course expert tools like SPSS and R, or IBM’s ManyEyes [25] for visualizations.

A picture of a continuous learning analytics process emerges, in which heterogeneous and ever changing data source applications provide relevant data for learning analytics, at the same time as questions of learners to data also continuously change. To support such a continuous analytics process, we have developed a generic visualization tool for multi-user, multi-application activity log data. In this paper, we describe the tool as well as the results of a task-based comparative evaluation for the use case of reflective workplace learning. The generic visualization tool integrates data from heterogeneous sources in comprehensible visualizations. It includes a set of visualizations which are not designed for specific data source applications, thus the term *generic*. It can visualize *any* activity log data published on its cloud storage. The only prior assumptions are that every entry in the data should be: i) time stamped and ii) associated with a user. The tool thus strikes a balance between generality (few prior assumptions) and specificity.

One key concern was whether the developed generic visualizations tools would be as comprehensible as those designed specifically for a given application or dataset. In this paper we describe an experiment comparing the performance of study participants along learning analytics tasks given the generic visualizations and visualizations custom-designed for the respective data.

2 Related Work

Others before us have pointed out the need to collect and analyze data for learning across users (multi-user) and applications (multi-application), both in the community of learning analytics and open learner modeling: Learning analytics measures relevant characteristics about learning activities and progress with the goal to improve both the learning process and its outcome [16,23]. Open learner models collect and make intelligible to learners and in some use cases also to peers and teachers data about learning activities and progress as well, again as basis for reflection on and improvement of learning [4]. Also in user modeling, the visualization of data across users is a relevant topic (e.g., [14]). Clearly, relevant characteristics about learning activities reside very rarely only in a single system, and both communities have identified a need to collect and analyze data from

heterogeneous data sources [12,18]. For instance, in Kay and Kummerfield [13] a variety of external data sources (mainly health sensor's data) is used for aggregation, analysis and visualization (through external applications) to support completing Sisphean tasks and achieving long term goals.

Visualizations in learning analytics and open learner modeling play the role of enabling users (most often students, teachers, but also institutions or policy makers - cf. [23]) to make sense of given data [6]. Most papers, however, predefine the visualizations at design time, in full knowledge of the data sources [6,10,14,15,20,21]. In Kay et al. [14] for instance, teams of students are supported with open (team) learner models in learning to develop software in teams. The authors developed a set of novel visualizations for team activity data, and showed the visualizations' impact on team performance (learning). In Santos et al. [22], student data from Twitter, blog posts and PC activity logs are visualized in a dashboard. The study shows that such dashboards have a higher impact on increasing awareness and reflection of students who work in teams than of students who work alone. Again, data sources are defined prior to developing visualizations however. In such visualizations, users "simply" need to understand the given visualizations, but do not need to create visualizations themselves.

On the other end of the spectrum are extremely generic data analytics tools such as spreadsheets or statistical analysis tools like SPSS or R. Outstanding amongst such tools is probably IBM's web-based tool ManyEyes. Users can upload any data at all in CSV format, label and visualize data. ManyEyes makes no assumptions at all about uploaded data, but clearly puts the burden of figuring out what kind of visualizations are meaningful to the users.

3 Generic Visualization Tool for Activity Log Data

We have developed a generic visualization tool for activity log data that addresses two fundamental challenges shared in many scenarios at the intersection of learning analytics, open learner modeling, and reflective learning on the basis of (activity log) data: Data from multiple applications shall be visualized; and at the time of designing the visualization tool, the concrete data sources and consequently the concrete analytic tasks are unknown.

3.1 A Priori Knowledge about Data

We make only two assumptions about data, namely that they are i) time stamped and ii) every data entry is associated with a user. The second assumption is useful because in a lot of learning scenarios, learning is social [1]: Students regularly work in teams as well as employees in organizations (in the context of workplace learning). Depending on the applications that are used to collect the activity log data, and the users' sharing settings, data from other users may be available. Therefore, it is reasonable to assume that meaningful insights can be gained by analyzing not only data from one individual but also data from multiple users.

3.2 System Architecture and Data Format

The generic visualization tool (Vis-Tool) is implemented as a client-server architecture. It is a web application implemented in HTML5/Javascript and Java. The Vis-Tool itself does not capture any activity log data, but is responsible for the visualization of the data in a sophisticated and meaningful way. Through its server component, it is connected to a cloud storage that stores application data and manages access to data. The data source applications store their activity log data on the cloud storage in so-called spaces: Private spaces store data of only one user, while shared spaces collect data from multiple users. Single sign-on provides a common authentication mechanism for all data-source applications, the Vis-Tool and the cloud storage. The rationale behind this chosen architecture is to deal with data collection, data analysis and data visualization separately. The Vis-Tool expects data in an XML format described by a publicly available XML schema. In addition, the schema must extend a base schema that contains a unique ID for all objects, a timestamp and a user ID as mandatory fields.

3.3 Single-Column Stacked Visualization

The Vis-Tool organizes visualizations in form of a dashboard style similar to [6,21,15,10], but we use a single column for the visualizations. Visualizations are always stacked on top of each other and share the same time scale, whenever possible. This is necessary to directly compare the data from different applications along the very same timeline (see Fig. 1). Users can add charts to their dashboard using an "Add" button. Charts can be minimized ("-") or completely removed ("x" button), which are located at the top right corner of each chart. The position of each chart can be rearranged by using drag and drop. Thus, a user can easily adapt the visualizations to one's individual needs.

3.4 Chart Types

The Vis-Tool provides four types of charts with different visual channels: geo chart, bar chart, line chart and timeline chart (see Figure 1).

The geo chart is used for data that contains geo positions. Besides the "latitude" and "longitude", the chart consists also of the "popup header" and "popup text" as additional visual channels. Both of them are shown in a popup window when clicking on an entry. The bar chart is available for any structure of data. It contains the "aggregate" channel and the "operator" setting. While the "aggregate" channel defines, which data property should be aggregated, the "operator" defines how the data will be aggregated (count, sum, average, min max) in order to be displayed. The line chart contains "x-axis", "y-axis", and "label" (on hover text). It is available for data with numerical data properties. Our timeline chart is similar to the line chart but does not have an "y-axis" channel. All charts have the "group by" channel. It defines how data can be grouped with the help of colors. For example, if we use a user id to group the data belonging to one user, all data captured by this user will be presented with the same color. If

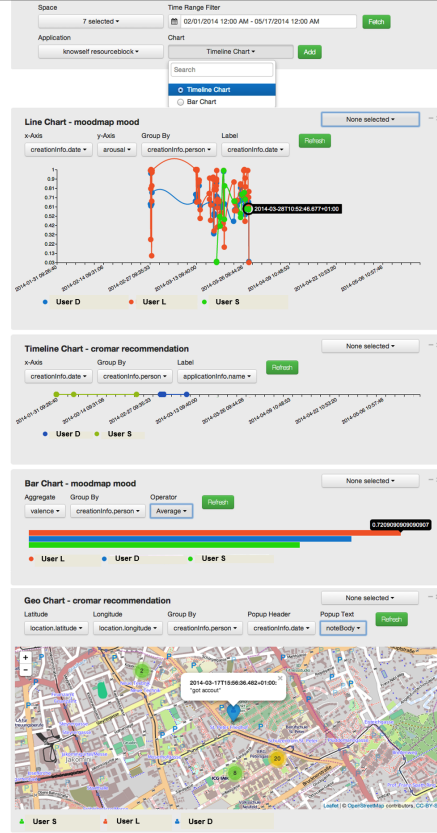


Fig. 1: Vis-Tool user interface (at the top) including four charts with user data in the single column dashboard.

several users are added to a group, all data captured by the users belonging to this group, will be presented with the same color. This feature makes it possible to easily spot user patterns across applications.

3.5 Mapping Data to Visualizations

Users create charts in the Vis-Tool by selecting data they wish to visualize, selecting a chart type, and then filling the chart's visual channels. The Vis-Tool, however, presents only those options to the user that are possible for any given data. Technically this is solved with chart matching and channel mapping.

3.5.1 Chart Matching For each chart type, we created a chart description consisting of a list of all channels, mandatory as well as optional, and the data types that the channels can visualize. At runtime, the XML schemas that describe the structure of the user data are parsed and the data properties including their data types are extracted. Based on the extracted data structures and the available channels per chart, chart matching is performed. The matching determines whether a chart is able to visualize a dataset described by a parsed schema.

This is done by checking for each channel of the chart, if the data structure has at least one property whose data type can be visualized by the given channel. For instance, the line chart consists of x-axis, y-axis as mandatory channels and the hover text as optional channel. The x-axis can visualize numeric values and date-time values and the y-axis can handle numeric values. The hover text channel is able to handle numeric values, date-times and strings. The line chart will be available for the parsed data structure, if the structure contains at least one numeric type or date-time for the x-axis and a numeric type for the y-axis. The hover text is an optional channel and therefore not of relevance for the decision, if the line chart is able to present the parsed data structure or not. For a given data structure, chart matching is performed for each chart type. Those chart types that match with the given data structures are added to the list of possible chart types and can be selected.

3.5.2 Channel Mapping Channel mapping takes place if a user selects one of the available charts. An initial channel mapping is automatically provided to the user when adding a chart to the visualization. Users can adapt the mapping of a property to another chart channel via the interface.

4 Use Case

The Vis-Tool can be used in any use case in which analysis of multi-user and multi-application activity log data makes sense. A lot of learning analytics and open learner modeling use cases fall into this category, as argued above. The task-based comparative evaluation that we subsequently describe and discuss in this paper assumes a specific use case however. It is one of knowledge workers who work in a team, carry out a significant amount of their work on desktop PCs, and spend a significant amount of time traveling. In the sense of reflective work-integrated learning [3,7] knowledge workers would log a variety of aspects of their daily work, and routinely view the log data in order to gain insights on their working patterns and change (for the better) their future working patterns. Concretely, we evaluate the Vis-Tool in comparison to three specific activity log applications that all have been successfully used and evaluated in the context of such reflective workplace learning [5,8,17].

Collaborative Mood Tracking - MoodMap App³ [8] - is a collaborative self-tracking app for mood, based on Russell's Circumplex Model of Affect [19]. Each mood point is composed of "valence" (feeling good - feeling bad) and "arousal" (high energy - low energy). The mood is stated by clicking on a bi-dimensional mood map colored according to Itten's system [11]. Context information and a note can be manually added to the mood, while the timestamp is automatically stored. Depending on the user's setting, the inserted mood is kept private or shared with team members. Mood is visualized on an individual as well as collaborative level. The MoodMap App has been successfully used in virtual team meetings to enhance team communication by inducing reflection [8].

³ <http://know-center.at/moodmap/>

Example analysis on MoodMap data for workplace learning are to review and reflect on the development of individual mood in comparison to team mood, and in relationship to other events or activities that happen simultaneously.

PC Activity Logging - KnowSelf⁴ [17] automatically logs PC activity in the form of switches between windows (associated with resources like files and websites as well as applications). Manual project and task recording, as well as manually inserted notes and comments complete the data captured by the app. The visualizations are designed to support time management and showcase in particular the frequency of switching between resources, the time spent in numerous applications, and the time spent on different activities. KnowSelf has concretely been used as support for improving time management [17], but activity logging data has also been used as basis for learning software development in an educational context [21,22]. Example analyses of PC activity log data for workplace learning are to relate time spent in different applications to job description (e.g., the role of developer vs. the role of team leader), and to relate the time spent on recorded projects to project plans.

Geo Tagged Notes - CroMAR [5] is a mobile augmented reality application designed to show data that was tagged with positions around the user's place. The information is overlayed on the video feed of the device's camera. CroMAR allows users to create geo-tagged data such as notes and pictures. The notes are stored in the cloud storage. CroMAR has features that are relevant for reflecting on any working experience with a strong physical nature. It was specifically developed for reflection on emergency work, in particular in relation to crowd management. CroMAR has been evaluated in the domain of civil protection to review, location-based, what happened during events [5]. A typical use case for knowledge workers would be to reflect both on the content of notes, and their relation to particular locations (which would typically be in line with customers, project partners, location-based events, or travel-related locations).

4.1 The Potential Benefit of Combining Data Across Applications

In prior work, we explored the potential benefit of analyzing data from PC activity logging data together with collaborative mood tracking data in such a use case [9]. As one example, a user's mood might drop consistently in relation to a particular project. In addition, we conjecture that mood might also be related to particular places, or some kinds of work might be carried out more productively outside the office.

5 Research Approach: Task-Based Evaluation

We performed an evaluation to compare custom visualizations in the data source applications (in-app) with generic visualizations (Vis-Tool). The goal was to establish how the comprehensibility of generic visualizations, designed without specific prior knowledge about (meaning of) data, compares to custom in-app visualizations that were customized for a specific kind of data and task.

⁴ <http://know-center.at/knowself/>

5.1 Data preparation

We prepared a test dataset with data about three users, called **D**, **L** and **S**, containing two weeks of data from all applications. To do so, we extracted data from real usage scenarios of the single applications. For MoodMap, we selected two weeks of the three most active users out of a four-week dataset. For KnowSelf, we selected three two-week periods of log data out of a 7-month dataset from a single user. For CroMAR, we used the dataset from a single user who had travelled significantly in a two-weeks period, and manually created two similar datasets to simulate three users. The data were shifted in time so that all datasets for all applications and users had the same start time and end time.

5.2 Evaluation Procedure

The evaluation is intended to test the comprehensibility of generic visualizations for learning analytics. We wanted to investigate how understandable are generic visualizations compared to the custom visualizations that are specifically designed for data of one specific application. Our initial hypothesis was that the generic visualizations could be as meaningful as custom visualizations. As we wanted to rule out confounding factors from different interaction schemes, we opted to perform the experiment on paper based mock-ups. These were created from the datasets by capturing screenshots of the in-app visualizations and the generic ones generated with the Vis-Tool. We prepared short analytics tasks (see Table 1) that participants should solve with the use of the given visualizations. The tasks are plausible in line with the chosen use cases (see Section 4) above, which were constructed based on use cases of knowledge workers that were previously evaluated in their working environment [8,17] as well as use case exploration of joint data analysis [9]. We simulated the hover effect, clicking, scrolling and zooming by first letting the participants state the action and then replacing the current mockup with a new corresponding one.

The evaluation followed a within-participants design. For each tool (MoodMap App (MM), KnowSelf (KS), CroMAR (CM)) we created a number of tasks (MM=4, KS=4, CM=2). We created variants of each task with different datasets for each condition (Vis-Tool, in-app). Thus, there were 20 trials per participant (10 tasks in 2 conditions for each participant). Tasks and tools were randomized across participants to avoid favoring either. We grouped the tasks by tool and randomized the order of groups, the tasks within groups and the order of condition (in-app visualization / generic visualization). The experimenter measured the duration (time to completion) and real performance for each task. Additionally, subjective scores of difficulty were measured through self-assessment using the NASA-TLX workload measure [9]. The tasks were organized in groups, each containing tasks with data generated from a single log activity application. Table 1 summarizes the tasks per tool.

The study followed the format of a structured interview, where the experimenter first explained the goals, the applications and the tasks participants would perform. The participant then proceeded to the first task, which finalized

T#	App	Task
1	MM	On the given day, to whom did belong the worst single energy (arousal) and to whom did belong the single worst feeling(valence)?
2	MM	On the given day, to whom did belong the worst average energy (arousal) and to whom did belong the worst average feeling (valence)?
3	MM	Find out on which day in the two recorded weeks was entered the best energy(arousal) and best feeling (valence) of the user!
4	MM	Find out on which days (dates) the MoodMap App was not used at all!
5	KS	On given day, when exactly (at what time) did the given user had the longest break? How long was the break?
6	KS	Find out on which day in the two recorded weeks did L work (regardless of breaks) longest?
7	KS	Find out which application was most frequently used in the last two weeks by given user!
8	KS	Find out which user used MS Word most often on the given day!
9	CM	(a) Find out where (in which Countries) in Europe have notes been taken! (b) Find out in which cities in Austria did L and D take notes!
10	CM	(a) Find out how many notes have been created at Inffeldgasse, Graz! (b) Find out how many notes have been created in Graz!

Table 1: Tools and evaluation tasks. **L**, **D** and **S** are the initials of the users to whom the data belong.

with the NASA-TLX. After finishing each group a questionnaire was distributed to directly evaluate the visual design, comprehensibility and user preference of in-app visualizations in comparison to the Vis-Tool visualizations.

5.3 Participants

Eight people participated in the experiment, all knowledge workers (researchers and software developers). Three of them were female, 5 male. 3 participants were aged between 18-27 and 5 were aged between 28-37.

6 Results

Overall, our study participants performed significantly better with the generic visualization tool in five (T2, T3, T7, T9, T10) out of ten tasks, worse in only one (T5) task and without significant difference when compared to the in-app visualizations in the remaining four (T1, T4, T6, T8) tasks. To analyze results, the Fisher’s Test was used to check the homogeneity of variances. The tf-test was used to test significance for cases with homogeneous variance. If not, the Walch-Satterthwaite test was used.

6.1 Workload

The NASA-TLX includes six metrics, which are considered scales of workload. We used the simplified R-TLX method to compute workload by averaging the scores. Figure 3 (MoodMap vs. Vis-Tool), Figure 4 (KnowSelf vs. Vis-Tool)

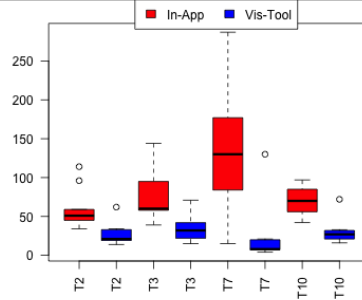


Fig. 2: Task duration (in seconds) for all tasks with significant differences.

and Figure 5 (CorMAR vs. Vis-Tool) show the box plots of the significant results for NASA-TLX metric: mental demand (MD), physical demand (PD), temporal demand (TD), measured performance (MP) and frustration (F) as well as the workload (W), computed as the average of all self-evaluation metrics and the measured performance (MP). Task duration (D) for all apps is given in Figure 2. The result of the t-test for T2 indicates that participants

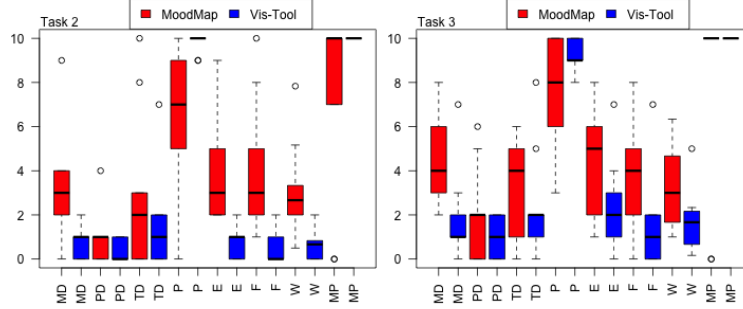


Fig. 3: MoodMap vs. Vis-Tool (T2,T3) - Significant NASA-TLX results.

experienced significantly less workload when using Vis-Tool than MoodMap, $t(9) = 3.17; p < .01$. Also, the task duration was significantly lower in the case of Vis-Tool, $t(9) = 3.18; p < .01$. In fact all individual metrics show significantly better scores in favor of Vis-Tool. For T3, there was a significant less workload and significant less duration when using Vis-Tool, $t(9) = 2.13; p < .05$ respectively $t(9) = 3.44; p < .01$. For T5, there was a significantly lower workload when

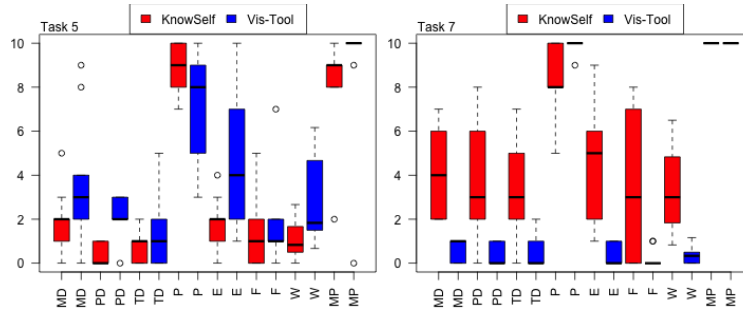


Fig. 4: KnowSelf vs. Vis-Tool (T5,T7) - Significant NASA-TLX results.

using KnowSelf in comparison to Vis-Tool, $t(9) = 2.21; p < .05$. Individual metrics show a significant difference in effort and physical demand (see Figure 4). For T7, except for measured performance (MP), significant differences were found in every other metric. Participants experienced significantly lower workload using Vis-Tool, $t(9) = 4.60; p < .01$. They also spent significantly less time solving the task with Vis-Tool, $t(9) = 3.64; p < .01$. In the group CroMAR VS Vis-Tool,

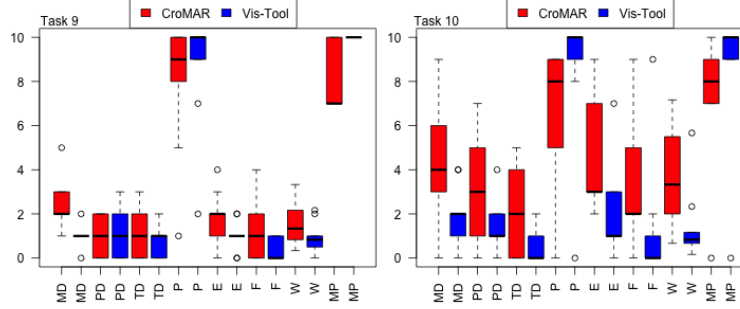


Fig. 5: CroMAR vs. Vis-Tool (T9,T10) - Significant NASA-TLX results.

the results of both tasks show significant differences in favor of the Vis-Tool (see Figure 5). For T9, there was a significant difference in measured performance, $t(9) = 3.16; p < .02$. Individual metrics show significant difference in mental demand. For T10, there was a significantly less workload when using Vis-Tool, $t(9) = 2.36; p < .04$. Analysis of individual metrics showed significant differences in mental and physical demand. Duration was also significantly different in favor of Vis-Tool, $t(9) = 4.68; p < .01$.

6.2 Application Preferences and Visual Design

The summarized results of the user preferences regarding the used apps for solving the given tasks are presented in Table 2. For the tasks T1-T4 and T9-T10 Vis-Tool was preferred over both MoodMap and CroMAR. For the tasks T5-T8 the results of Vis-Tool vs. KnowSelf were ambiguous. For T5 and T6 participants preferred KnowSelf whereas for the tasks T7 and T8 they go for the Vis-Tool. This correlates with TLX where users performed better using KnowSelf in T5 but much worse in T7.

The results of the question “How did you like the visual design of the visualisations for the given tasks?” (see Figure 6) showed a clear preference for the visual design of the Vis-Tool in comparison to the MoodMap (tasks T1-T4) and CorMAR (tasks T9-T10). In contrast, for the tasks T5-T8 they preferred the visual design of KnowSelf over that of the Vis-Tool. Regarding the question “How meaningful were the given visualizations for the given tasks?” the participants stated that Vis-Tool visualizations were significantly more meaningful for the given tasks in comparison to the MoodMap and CroMAR (see Figure 6). Interestingly, there were no significant results regarding Vis-Tool and KnowSelf.

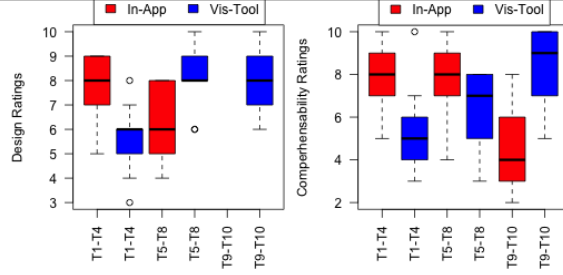


Fig. 6: User ratings on the design and comprehensibility of the visualizations.

	T1	T2	T3	T4	AVG	T5	T6	T7	T8	AVG	T9	T10	AVG
Vis-Tool	89%	78%	67%	44%	69%	22%	22%	100%	78%	56%	67%	100%	83%
In-app	11%	0%	0%	0%	3%	67%	56%	0%	11%	33%	33%	0%	17%
Both	0%	22%	11%	11%	11%	11%	11%	9%	9%	6%	0%	0%	0%
None	0%	0%	22%	44%	17%	0%	11%	0%	11%	6%	0%	0%	0%

Table 2: Which visualizations are preferred for solving the given tasks?

7 Discussion

Overall, the performance of study participants was satisfactory with the Vis-Tool, showing comparable and mostly even better performance when compared with in-app visualizations. In many cases, study participants had a significantly lower workload and were significantly quicker to solve the tasks using generic visualizations: Participants achieved significantly better results with the Vis-Tool than with the MoodMap App in two out of four tasks in terms of workload and time to task completion (T2, T3 - see also Figure 2 and 3), better results with the Vis-Tool than with KnowSelf in one out of four tasks (T7 - see also Figure 2 and 4) and better results with the Vis-Tool than with CroMAR in two out of two tasks in terms of task performance (T9) and workload and duration (T10 - see also Figure 2 and 5). These results are also confirmed by the answers of the questions regarding the comprehensibility of the visualizations with regard to the given tasks (see Table 6).

7.1 Supporting Analytic Tasks Beyond Design Time

These results are not a statement on the quality of design of the specific apps per se. All three used activity logging applications have successfully been used to induce and support learning in the workplace. Rather, the results are a function of whether the data source applications have been designed to answer the type of questions about data that study participants were asked to answer in the evaluation. The focus of CroMAR for instance was in location-related, augmented-reality-style, visualization of geo-tagged data in order to support situated reflection on events [5]. Quite naturally then, its user interface is less conducive to answering general questions about data. The focus of KnowSelf on the other hand was to support users in reviewing their time use daily in order to support time management [17]. This is visible in the comparative results which show a strong task dependence: Participants find it easier to perform the task that relates to a single day (T5) with KnowSelf than with the Vis-Tool, but find the

Vis-Tool more supportive in a task that relates to a longer period of time (T7). Another example of generic visualizations adding benefit to in-app visualizations is that the data source applications had different support for multiple users: KnowSelf is a purely single-user application; nonetheless, there is a plausible interest within teams to know how others in the team use their time. CroMAR visualizes data from multiple users but does not visually mark which data comes from which user, and MoodMap App is a real collaborative tracking application. Our study results therefore clearly showcase that and how generic visualizations can add benefit to in-app visualizations when users want to solve analytic tasks beyond those that were known at application design time.

7.2 Visualizing Derived Data Properties

A limitation of the current implementation of the Vis-Tool is, that it is only able to display given properties, but cannot calculate new values. For instance, in KnowSelf, the data entries contain the start and the end time but not the duration. The visualizations in KnowSelf make use of such derived data properties: As KnowSelf developers know exactly what kind of data were available, they could also easily implement calculations based on given data and use these for visualizations. In the Vis-Tool on the other hand, we have in general too little prior knowledge about data to automatically perform meaningful calculations on data in order to compute “derived data properties”. Technically, it would be possible to extend the Vis-Tool’s user interface such that calculations on given data can be specified, but we assume that ease of use would be rather difficult to achieve. In addition, such functionality would increasingly replicate very generic spreadsheet (e.g., Excel), statistical analysis (e.g., SPSS) or visualization (e.g., ManyEyes) functionality. It might be easier overall to shift the burden “back” to data source applications, in the sense of requiring data source applications to provide derived values that are of interest themselves.

7.3 Ease of Interaction

In this work we have focused on the comprehensibility of visualizations. We did not formally evaluate the user interaction itself, i.e. the process of creating a specific visualization. However, we are aware that the Vis-Tool requires users to become familiar with concepts such as mappings and visual channels.

A plausible emerging scenario is to differentiate between two user roles: One role (expert) would be responsible for creating a set of meaningful visualizations. The expert would know concretely which data source applications are available and what kind of analytic tasks users will want to solve. This person does not need to write code, but needs to have some training or experience with the Vis-Tool. The set of meaningful visualizations would be stored and serve as pre-configuration for learners. A second role (learner) would then only need to load a pre-configured set of visualizations and “use” them, similar to the study participants in the task-based evaluation discussed in this paper. Of course, users would have the freedom to explore the mapping interface if interested, and

generate new visualizations. Based on this overall scenario, more complex usage scenarios for generic visualization tools like ours could be elaborated that involve for instance sharing and recommending dashboards.

8 Conclusion

We have developed a generic visualisation tool for activity log data that addresses two fundamental challenges shared in many scenarios at the intersection of learning analytics, open learner modelling, and workplace learning on the basis of (activity log) data: Data from multiple applications shall be visualised; and at the time of designing the visualisation tool, the concrete data sources and consequently the concrete analytic tasks are unknown. The Vis-Tool makes only two assumptions about data, namely that they are time-stamped and are associated with users. The comprehensibility of the Vis-Tools visualisations was evaluated in an experiment along data analytics tasks that were designed on the background of workplace learning. This evaluation was carried out within the target user group of knowledge worker, and based on real-world data. It thus constitutes firm ground, also for other researchers, to compare the suitability of other generic visualisations with, or to proceed with the next step in the design process for such a generic visualisation tool, namely the design of the user interaction process.

Acknowledgments

The project “MIRROR - Reflective learning at work” is funded under the FP7 of the European Commission (project nr. 257617). The Know-Center is funded within the Austrian COMET Program - Competence Centers for Excellent Technologies - under the auspices of the Austrian Federal Ministry of Transport, Innovation and Technology, the Austrian Federal Ministry of Economy, Family and Youth and by the State of Styria. COMET is managed by the Austrian Research Promotion Agency FFG.

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Reflection Analytics in Online Communities: Guiding Users to become active in Collaborative Reflection

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Abstract: As reflection helps practitioners to turn experiences into learning, communities of practices provide an environment to support reflection. We present a concept showing how reflection analytics in online communities of practice can help users to improve their reflection activity, guiding them to become active reflective participants. A prototype shows how our concept will be evaluated.

Keywords: reflection, reflection analytics, learning analytics, community of practice

1 Introduction

Reflection is a common activity at workplaces [1]. Our understanding of reflection is based on Boud, who describes it as a process with three steps: returning to past experiences, reassessing them in order to learn something for future actions [2]. While most research focuses on individual reflection or reflection in educational settings, we focus on collaborative reflection by a group of professionals at work, showing how reflection helps these groups to learn more than they could individually [3].

In earlier work, we have found that small groups of reflective participants (see 2.1) might suffer from a lack of time or the willingness of other group members to actively and frequently engage in reflection, and therefore, in line with [4], we propose to support collaborative reflection in communities of practice [5]. A community of practice is comprised of members doing similar work, e.g. working in a certain job role, and who have similar practices [6]. Although communities of practice can be informal and loosely organized, a community of practice is often supported by Information and Communication Technologies (ICT) such as online portals with discussion boards enabling members to exchange practice [6].

From an organizational perspective, enabling workers to reflect together through a community of practice has multiple benefits [6]: newer employees can benefit from the expertise of experienced workers, practitioners can discuss and share tacit knowledge, and spatially distributed organizations can connect employees working in different geographic locations. We found that integrating reflection support into

community tools provides benefits compared to offering standalone reflection tools, as the former integrates reflection into existing communication practices [7].

In the ‘work in progress’ approach presented in this paper, we aim at developing initial “reflection analytics” to guide reflection by participants in communities. We lean on the field of learning analytics, to capture and present the activity of learners to support reflection on their personal learning [8]. This approach has been proven effective for informal learning, and we believe such an analytics driven approach will also be effective in supporting reflective learners in communities.

This paper combines the concepts of collaborative reflection, communities of practice and provision of guidance to users in becoming reflective learners. In this paper, we describe our concepts, their corresponding background and an initial prototype.

2 Related work

2.1 Group dynamics in collaborative reflection

Models of reflection have been developed by Schön [1] and Boud [2] focusing on the individual. In practice people often discuss their experiences together and thus reflect together [3]. To engage in this collaborative reflection, participants need to communicate and discuss their experiences, which is at the core of reflection [7]. This is important for individual workers as well as for organizations [8].

In previous work we have analysed tools supporting groups reflection. We found that users assume roles based on the core activities of documenting, commenting and reading about different experiences, and that collaborative reflection depends on the distribution of these roles in groups. We found four basic roles [9]:

- **Documenters:** Users focussing on documenting experiences.
- **Commenters:** Users who comment mainly on other’s documented experiences.
- **Readers:** Users reading many shared experiences and associated comments, but rarely becoming active by writing experiences or commenting on them.
- **Typical (full) reflection participants:** Ideally, users participate equally in all three activities (see above), thus actively supporting the reflection in the group.

In our analysis we found that active reflection groups either contained a core of typical reflection participants or a sample of enough documenters and commenters to provide activity in the reflection groups. We concluded that activating readers to start documenting and commenting as well as motivating commenters to document and vice versa is likely to increase reflective learning in the respective groups [9].

2.2 Group dynamics in communities of practice

Communities of practice offer opportunities for informal learning through facilitating discussions by members around practice, exchanging practices and experiences [6]. By being active in such exchange, learners can reflect upon how to integrate shared practices and experiences into their own daily practice. This is similar to support for

collaborative reflection, and the roles undertaken in communities of practice show further similarities.

In their classic model of how users interact in communities of practice, Lave and Wenger differentiate between a periphery comprised of new members or members with low levels of activity and the core of the community with a low number of highly active members [10]. Karalis [11] adds additional levels, ranging from passive observers to transactional and peripheral participants as well as those at the core. A common role often found in the periphery or passive zone of communities is that of a “Lurker” [12], similar to the readers we described above. In their concept of legitimate peripheral participation, Lave and Wenger emphasize the positive aspect of lurking (reading) as a way of getting to know the community before becoming active, and of learning from others’ experiences [13].

Welser et al. [14] and Jones et al. [12] included in their typology “answer people”, who mainly answer other users posts instead of writing their own, in a similar way to our description of commenters. Answer people are not connected to many members in the community, and interact on the periphery of a community. They can be seen as peripheral participants in the Karalis model. Furthermore, an analysis of the medical support community WebMD, by Introne, Semaan and Goggins [15], suggests that active core members spend a lot of time talking to new users. This suggests that active core members may play our commenter role. Users who are only active occasionally seemed to play the role of documenters (posting new content in the community). However, these findings may be specific to the particular type of community investigated, as users of WebMD seek advice around diseases rather than sharing practices.

Research is also concerned as to how people transition from the periphery of the community towards the core. An interesting model can be found in the Reader-to-Leader model [16], which states that by contribution (e.g., enough interesting and valuable content) and with motivation (e.g. recognition by others) users may increase their activity from being a reader to being a leader supporting others in communities.

2.3 Learning Analytics

Learning Analytics focuses on helping learners to understand their learning progress and optimising their learning, by a data driven analysis of action undertaken in learning environments [8]. However, most learning analytics research and practice has been undertaken in formal school and university contexts. Critically, much workplace learning is informal with little agreement of proxies for learning. While learning analytics in educational settings very often follow a particular pedagogical design, workplace learning is much more driven by demands of work tasks or intrinsic interests of the learner, by self-directed exploration and social exchange that is tightly connected to processes and the places of work [17]. Learning interactions at the workplace are to a large extent informal and practice based and not embedded into a specific and measurable pedagogical scenario.

Pardo and Siemens [18] point out that “LA is a moral practice and needs to focus on understanding instead of measuring.” In this understanding “learners are central agents and collaborators, learner identity and performance are dynamic variables,

learning success and performance is complex and multidimensional, data collection and processing needs to be done with total transparency.” This poses issues within the workplace with complex social and work structures, hierarchies and power relations.

Buckingham Shum & Ferguson [8] have added a focus towards the social aspects of learning including how learners interact with each other. The focus on the social aspect of learning analytics is more congruent with the informal and social nature of learning in communities of practice. Data is presented in a way to allow learners to take action upon it (actionable data). Showing learners analysis of their own behaviour can help stimulate reflection [8]. De Laat & Schreurs [19] demonstrate how social network analysis (SNA) and content analysis can contribute to learning analytics in community settings.

3 A concept to support reflection analytics

Our concept aims to balance the structure and roles in a community with respect to becoming an active reflective participant. The goal is to help users to transition from a reading role at the periphery to a more active role near the core of a community. To achieve this, we will deliver personal and group reflection (learning) analytics combined with personalized facilitation depending on the analytics, making users aware of their current reflection activities.

For this kind of scaffolding, we have to know which role a user is playing while reflecting in a ICT supported community of practice. For this we build on the metrics we used in our previous work on roles and groups in collaborative reflection (e.g. number of comments per time span, [9]) as well as through social network analysis ([19] and [15], who published an algorithm for SNA), which may help us to analyse interactions in collaborative reflection, and [12], who describe various metrics for online discussion forums to measure the activity of users. This work enables us to analyse the activity of users in real time and to compare it to their peers. Using this analysis, we can support each user type differently:

- **Guiding typical reflection participants:** Participants can be shown new or less popular threads to help users by providing their experiences as described in [15].
- **Guiding documenters:** Documenters are likely to have experiences that are helpful for others, and therefore should be encouraged to comment on other users’ posts to enable reciprocity in the community. When receiving help by others, they could get encouraged to help others in turn.
- **Guiding commenters:** Users who often help others by commenting on posts can be encouraged to also create an occasional post themselves to provide experiences others can relate to in order to foster activity as described by [16].
- **Guiding readers:** Users who are reading a lot can be encouraged to start interacting with the community by for example asking questions to others about issues in their work life (see [20], who describe this as easier than answering; at least in Question and Answer forums). Readers also need to be made aware of the value their comments and posts may have for others. It is important **new users** are supported in order to ease them into using the platform and discussion area.

4 First Prototype

Our concept of support for these roles includes two steps. Firstly, we provide reflection analytics to make users aware of the role they currently play and secondly, we provide actionable prompts in the form of texts or images (related to activity prompts as mentioned in [21]) to users, proposing steps they can take to develop their role in the community like helping others or sharing own issues. Prompts have shown to be helpful in learning contexts [21, 22] to stimulate recipients to think about their actions, and we have developed a concept for prompts for collaborative reflection [5].

Our concept is currently work in progress and we have developed a prototype to evaluate it in practice. Fig. 1 taken from the prototype shows the three different individual roles in reflection as posts (new threads the person started, measuring documenter activity), comments (threads the user commented on, commenter activity), and reads (threads which the user looked into, reader activity). Fig 1. shows that the current user is reading more than average, writing an average number of comments, but is not writing many new posts. The prompt displayed in Fig. 1 suggests sharing own experiences, since the analytics shows the user is more of an answer-type person commenting on others threads.

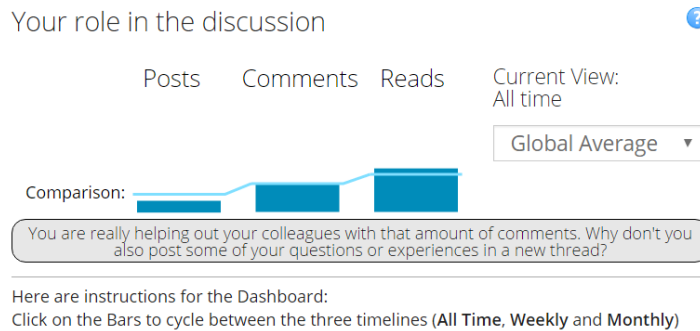


Fig. 1 Reflection analytics prototype

While the prototype is in its early stages, we are planning to extend it to implement and evaluate our concept. For example, we will develop the choice of prompts to analyse not only absolute numbers, but also trends in use and to inform users. Analysing the content created by a user may help us to identify whether the user is really taking part in collaborative reflection within a discussion (see our other work [23]), which might improve the choice of prompts, and it may allow us to understand user's interests. With the latter information, we may utilise recommendation engines to improve the choice of prompts, for example by recommending specific threads instead of telling new users to simply read something in order to get used to the community. Also it might be interesting to analyse whether user prefer to see their development over time in the community or rather this snapshot-based visualisation.

As we are currently finalizing the work on the prototype, we will be able to show and discuss these features at the ARTEL workshop. Subsequently we will evaluate the prototype in a real work environment to understand whether and how it influences user behaviour and whether and how this influences reflection in the community.

5 Conclusion

While our work is still in progress with no evaluation having been conducted to date, we are convinced that our idea of reflection analytics contributes to the overall work being done in the context of (AR)TEL. It builds on a solid basis of our own and other research and is likely to help users to understand and improve their reflection activities in what will then be *reflective* communities of practice.

6 Acknowledgements

This work is part of the EmployID (<http://employid.eu>) project on “Scalable & cost-effective facilitation of professional identity transformation in public employment services” supported by the EC in FP 7 (project no. 619619). We thank all colleagues and associated partners for their cooperation and our fruitful discussions.

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Visualizing online (social) learning processes – Designing a Dashboard to support reflection

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Abstract. Learning analytics, as a means to visualize learning, has been repeatedly suggested to enhance learners’ and teachers’ self-reflection in online learning processes. Departing from this notion, we propose a combination of this visual approach to learning analytics with the concept of social presence, thereby acknowledging social aspects of online learning processes that are often overlooked. More specifically, we present the considerations and design of a dedicated dashboard that supports self-reflection by visualizing (social) online learning processes. The approach is based on our belief that visualizing learning by itself does not automatically lead to self-reflection and awareness among students and teachers. Instead, organizers and instructors of learning activities need to be conscious about the social aspects of learning.

Keywords: Dashboard, reflection, social learning, online learning, awareness, visualization, learning analytics, social presence

1 Types of Learning Analytics – A German Perspective

The current discussion on learning analytics is based on two main approaches: The first approach focuses on the possibility of using learning analytics as a means to visualize learning, create awareness and stimulate self-reflection [1, 2]. The second approach centres around the idea of stimulating learning through programmed instruction (e.g. adaptive systems) by guiding learners through the learning process [3, 4]. Hence, it can be stated that the role of technology within these two approaches is different. While the latter approach assigns technology a more active role – intervening and guiding the learning process – the prior approach focuses more on technology as a formative tool – visualizing the learning activities in order to stimulate reflection and awareness of the underlying learning processes [5].

When considering the German discussion about this topic, the technology-driven approach is widely criticised and often even rejected as a methodological approach to inform students and teachers. Among the most commonly mentioned reasons for this position are concerns about privacy issues and, more importantly, doubts about employing an automated system to influence and intervene into the learning process of individuals. Consequently, the visual approach to learning analytics appears to be a more promising point of departure

when considering the implementation of such systems in a German context.

Dashboards are a frequently used and investigated tool in learning management systems to visualize learning activities. They consist of dedicated pages or areas within the system mirroring the personal learning process and thereby contributing to the perception and reflection of underlying learning processes. [6] Moreover, departing from the community of inquiry framework (CoI), it is possible to make other participants in a learning environment visible at all three levels: cognitive presence, social presence and teaching presence [7].

However, we believe that visualizing learning by itself does not automatically lead to self-reflection and awareness among students and teachers. Instead, drawing on recent concepts of online learning, like the CoI or the 3C model, the social dimension of learning might need to be emphasized more strongly. Accordingly, we argue that organizers and instructors of learning activities need to be conscious about the social aspects of learning. Many systems seem to focus on the interaction between the learner and the technology (e.g. often the Learning Management System wherein the learning activity is hosted and provided). We propose to extend this approach and to also incorporate the social aspects and interactions between learners in the visualization of learning, thereby providing a more complete representation of the underlying learning processes. It is the aim to contribute to the personalization of a learning environment [8].

Both concepts, the CoI as well as the 3C model, distinguish between three aspects of learning. While the CoI model focuses on three kinds of presence, namely teaching presence (e.g. direct instructions), social presence (e.g. emotional expressions, group cohesion, open communication) and cognitive presence (e.g. triggering events and exploration) [7], the 3C model has a somewhat different focus. Following this model, an online course consists of content (e.g. various kinds of presenting information), construction (e.g. learning tasks) and communication (e.g. video conferences, chats and/or forum discussions) [9]. To some extent, those models share the same perspective on online learning: beside emphasizing the social dimension of learning they mention its cognitive component, as well as the need for instruction. Accordingly, dashboards to mirror a social learning processes consists of three components containing visualizations of those dimensions.

Previous research explored a link between social interaction in learning management systems (LMS) and learners' social presence. Among others, Hölterhof and Rehm (2016) combined the results of social network analysis and social presence, in order to determine learners' position within a communication network and relating this to their (social) experiences within the LMS in question. More specifically, the authors were able to unveil different dimensions of social presence, especially pointing towards positive as well as negative social emotions. While research often focuses on positive emotions, both sides of socio-emotional awareness of other learners are important for a technology enhanced social learning process, especially if learning is considered as an inquiry process. [10]

Following this approach of not assessing learners experience of social presence but to visualize the social heterogeneity of learning as a group inquiry process, the advances of learning analytics turns towards transparency in providing these type of results to all relevant actors in the learning process (e.g. learners and teachers).

In order to take into consideration both the course structure on the one hand and social processes within the structures on the other hand, we develop a dashboard based on the aforementioned 3C-model.

2 Designing a Dashboard to Visualize (Social) Learning Processes

Departing from the aforementioned considerations and stipulations, we identified a high potential for a technology based solution to support and raise awareness in the context of enabling social presence (experiences). Consequently, we are in the process of designing a learning analytics dashboard, which is envisioned to become a feedback instrument, supporting learners in self-reflecting their learning progresses. The dashboard is integrated in a social learning management system based on the content management system (CMS) Drupal®, which is enriched by numerous features to enable communication and collaboration between learners and teachers [11, 12]. The system is further extended by a range of customized modules that visualize the underlying social and cognitive learning processes. Drawing on the 3C-model of online learning, digital learning contains of three different types of structural elements: content, construction and communication. The dashboard depicts all three elements of the model and is based on a selection of different applicable variables. The selected variables per category arise from the various affordances that the LMS offers. The content component visualizes the usage of learning materials available to learners, like text documents, interactive trainings or videos. Especially clicks on learning materials are considered to represent its usage. The constructive component mirrors learners' behavior in relation to the learning assignments. Visualizations within this component present the number of learning tasks per course unit, the number of submissions per task and the number of tries per person in order to solve a learning tasks. The communication component can be considered as rudimentary perspectives on social structures similar to what social network analysis investigates. They offer interpersonal communication, including number of posts in a discussion forum, comments per post and a distribution of posts per role (teacher and learner). Table 1 gives an overview of other variables, which will be presented within the dashboard.

In order to enable a possible transfer of the dashboard into other CMS and LMS (e.g. Moodle), the chosen variables and database structure have been constructed to enable this interoperability.

“Content” variables	“Construction” variables	“Communication” variables
Number of learning materials	Number of learning tasks	Number of discussions/ posts
Usage of learning materials	Number of submissions per learning task and person	Number of comments per post (in average)
Proportion of usage	Table: Number of tries per person in order to solve a learning task	Distribution of posts per role (teacher / learner)
	Number of persons per number of completed learning tasks	Percentage of posts and comments per role (teacher/ learner)
	Number of persons who only needs one try to pass the task	Wordcloud with frequent words

Table 1. Dashboard variables

The dashboard will be piloted in the context of two online master study programs at a German University, which are designed as in a blended learning course format.

The programs focus on online-learning- periods, which last at least nine weeks and up to twelve weeks in which three weeks form a unity. During this time, participants communicate with each other and engage into learning activities within the applicable LMS. Ultimately, the goal of this instrument is to stimulate course (activity) by enhancing transparency of (social) learning activities at different points in time. After each three-week course unit, students and teachers will be able to voluntarily access the current visualization of what activities took place. This in turn creates an opportunity for all participating actors (e.g. learners and teachers) to self-reflect about their learning behavior. It also relates effective data to previous points in time as well as previous courses. A visual representation of an initial wireframe is provided in Figure 1 below.

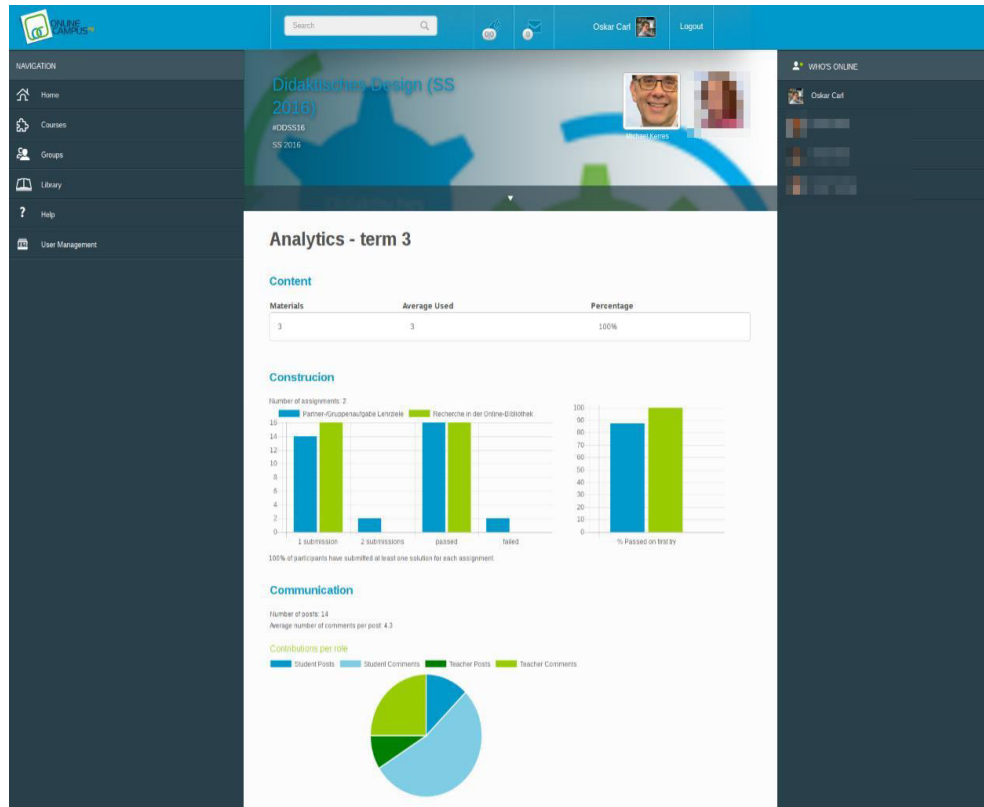


Fig. 1. Initial Wireframe of Dashboard

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E-portfolio for Awareness and Reflection in a Blended Learning Environment

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Abstract. Kelluwen is a learning community composed of teachers, students and researchers who are devoted to assessing and promoting ICT-mediated learning strategies, focused on improving students' socio-communicative skills. Kelluwen has a Web platform (<http://app.kelluwen.cl>) that supports b-learning activities allowing teachers to create, use and share instructional design leveraging Web 2.0 tools. This paper presents the development of an e-portfolio to be included in the Kelluwen platform, which aims at improving the support for awareness and reflection processes of students and teachers during their didactic experiences. Considering the requirements of the learning community, the e-portfolio is divided into four sections: Works, Evaluations, Statistics and Work's Gallery. The tool developed is evaluated in a pilot experience and we conclude that it enriches the learning processes by facilitating their comprehensive evaluation.

Keywords: e-portfolio; web 2.0, awareness and reflection.

1 Introduction

Kelluwen is a learning community the purpose of which is to improve the communication skills of elementary and high-school students introducing the use of collaborative web tools and social networks in learning processes, combining online and face-to-face (b-learning) didactic activities [16]. Under this context, the Kelluwen team has worked closely with teachers and education researchers in the development of relevant didactic designs. A didactic design (DD) is a type of instructional design based on social web tools that allows students to work collaboratively, post the outcomes of their learning and get feedback [4]. In addition, the Kelluwen web platform includes several communication and content management tools to support the *didactic experiences* of students and teachers when they run a DD. ([2], [11] and [17]). Kelluwen team proposes a comprehensive evaluation strategy of socio-communicative skills that involves awareness and reflection about the learning process by students and teachers. From the perspective of evaluator agents, the evaluation strategy includes the application of the following types of self-evaluation guidelines: metacognitive, co-

evaluative (joint evaluation) and hetero-evaluative (teacher to students) for the collaborative work. However, before this work, only peer-assessment was supported in the platform, while the rest of the evaluative processes were performed with guidelines available as files or hardcopy.

This work seeks to enrich the web platform, considering the peer-revision module with new features that support the application of different evaluative strategies, including views to facilitate the awareness and reflection of both students and their teachers about the learning process. The new tool being developed is an e-portfolio, which in addition to supporting a comprehensive evaluation process, provides both teachers and students with a space to manage all the products developed in a didactic experience.

The question that guides this research is the following: Can the proposed e-portfolio tool make a contribution to students' and teachers' awareness and reflection processes about their didactic experience?

2 Related Work

2.1 Evaluation Typologies

There are several ways of classifying evaluations. The most common classifications consider aspects such as functionality, timing or who evaluates [5]. This work considers the typology that classifies *evaluation by its agents*, i.e. based on the individuals who evaluate in each case. According to this criterion, the main types of evaluations are self-evaluation, co-evaluation and hetero-evaluation. To complement these types of evaluations, in Kelluwen we have also adopted i) *Product co-evaluation*: an evaluation performed by a group of students of a product generated by a second group of students. This type of evaluation is critical in the didactic activities proposed in Kelluwen [18], ii) *Eco-evaluation*: This evaluation is the one performed by a person of the environment in which the activity or phenomenon to be evaluated took place [10]. In Kelluwen, this is the evaluation of the learning experience by the student.

2.2 Best Practices in the Use of E-Portfolios

The concept of e-portfolio has several directions. While some articles define e-portfolio as a platform for the organization of student-created artifacts [2], others conceive it as an evaluation tool ([8] and [9]). In spite of these differences, several best practices can be recognized in the e-portfolio literature, as presented below.

Reflection mechanism introduced in the e-portfolio: A common factor is the use of the e-portfolio to improve learning by reflection. For instance, in [7] students are provided a space in their e-portfolio to write their reflections. Included are reflections on learning objectives, learning outcomes, attitude facing learning, peer performance and their evaluations. In [6], the student must develop a reflection on each artifact posted in his/her e-portfolio. In addition, there is a final evaluation where the student must reflect on the entire process. Several e-portfolios include reflection as an evaluation

object. For instance, in [9] there is a student self-evaluation instance to generate her self-reflection about his/her artifacts and opinions in the support platform forum. The number of reflections about other works and the time students devote to them is also evaluated.

Register of evaluations as part of the e-portfolio: A common trend is observed in terms of registering evaluations in the same e-portfolio. In [7] there is a section devoted to evaluations where students sign into “E-portfolio evaluation” which provides online forms to perform self-evaluations and co-evaluations. Similarly, the teacher can perform the hetero-evaluation in the same tool. Additionally, [6] provides tools to evaluate the reflections by students using the “Chinese Word Segmentation System” which classifies the type of reflection made.

Sharing e-portfolio artifacts: E-portfolios encourage the sharing of works and provide tools to collect critical feedback from other students. In [13] there is an area for presenting the best projects where students can easily access their classmates’ work. This area is called “Gallery” and it allows students to search works based on a set of criteria, including valuation, date, visits, student, course and semester.

Finally we remark that we use the concept of e-portfolio in the sense of an space to organize the processes and outcomes of learning activities during a limited period of time and not in sense of life-long e-portfolio.

2.3 Awareness and Reflection in b-learning Environments

[14] performs a systematic revision related to awareness and reflection processes in b-learning environments, stressing that most studies focus on the monitoring and visualization –by teachers– of their students’ learning process, with little research focused on supporting students in the awareness and reflection of their learning process, nor on providing teachers with information about their own practice. Within this small set of studies there is [12], which presents an extension of the WebLearn platform, the design of which is focused on providing students with support for their awareness and reflection processes and on providing teachers with information to review their own teaching practice.

3 Kelluwen E-Portfolio

Considering the main best practices in the use of e-portfolios found in the literature and the requirements of the community of teachers who have participated in Kelluwen, four modules were developed in the e-portfolio: Works, Evaluations, Statistics and Work Gallery. A stable version of the platform that includes the Portfolio is found in <http://app.kelluwen.cl/>, accessible through a simple register. Below is a description of the Evaluation and Statistic modules, given their relevance in the awareness and reflection about the learning process of students and teachers.

3.1 Evaluations

In this section of the e-portfolio, the Student View allows access to the different types of evaluations, depending on the activity that is being performed. Fig. 1 shows the module in which the evaluation displayed are team performance and work assessments. A simple diagram represents the evaluations with arrows between the student and her team mates. Each evaluation has a guideline, for instance, the team performance evaluation includes questions like: “She was responsible in fulfilling tasks”, “She helped his groupmates when they needed” or “She contributed to the group learning process”. In the case of work assessments, the questions are more specific to the subject area: “It is included in the slideshow a reflection about the conflicts experienced during the study period” or “A previous organization is observed in carrying out their slideshow”. In the experience assessment, there are more general questions: “The learning experience managed to satisfy a present need in your schooling” or “You think that criticism of the twin classrooms serve you to guide your learning”. Each guideline includes a space to make comments or explain the achievement levels assigned. The role of this open comment is to promote the students’ reflection process.

3.2 Statistics

This section deals with statistics or analytics of the results of the evaluation processes, considering visualizations that summarize the evaluations that each student or group gets from the different stakeholders involved, using two types of charts: i) histograms that show the frequency of each achievement level considering aggregated criteria of the evaluation guidelines; ii) radial chart that represent the most frequent achievement level for each disaggregated criterion. Additionally, different comparisons are made based on the type of evaluation: when dealing with performance assessments, self and co-evaluations are compared, while in the case of product evaluations, peer evaluations are compared with the evaluation performed by the teacher (see Fig. 2). When evaluating the experience, the evaluation of all students are compared.

4 Results of the Pilot Survey

During 2015, a pilot experience in the use of the Kelluwen Portfolio was conducted in two ninth grade twin classes at the Laico High School (classroom 1) and Martin Luther King High School (classroom 2), both in the city of Valdivia. The DD applied was “Building a Slide Show about the 2nd Half of the Twentieth Century” in the subject of History, Geography and Social Sciences. A total of 60 students, 31 from classroom 1 and 29 from classroom 2, arranged in nine groups per classroom, participated in the experience that took place during October 2015.

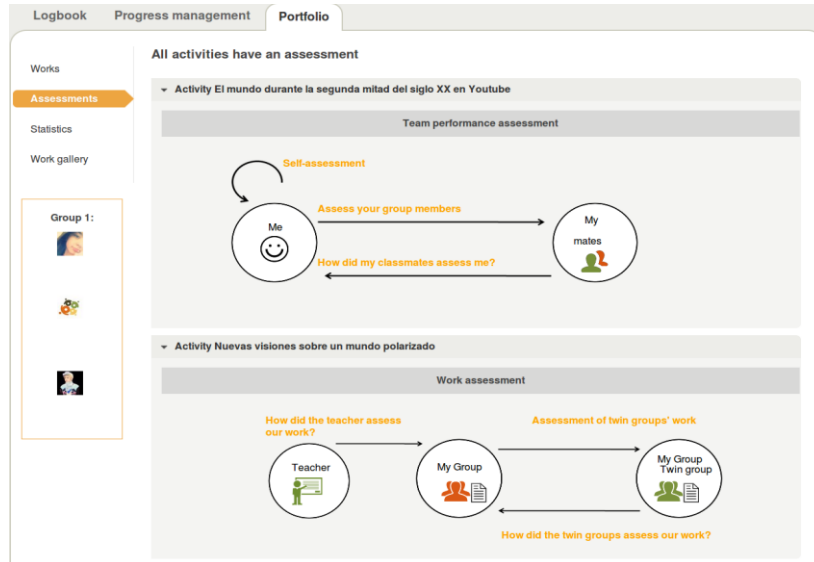


Fig. 1. Student View of Evaluation Section with Team Performance and Work Assessments.

Both teachers developed all the activities with their students, including all the proposed evaluation instances. All the groups posted works (68 in classroom 1 and 167 in classroom 2). During the experience, three activities of the Design were related to the evaluation, as follows: i) group co-evaluation, where 21 students in classroom 1 (68%) and 23 in classroom 2 (79%) completed the evaluation of their group mates; product co-evaluation where the 18 groups were assigned to reviewers between classes (twin classes) and completed the evaluation; iii) eco-evaluation, where nine students from classroom 1 (29%) and 25 from classroom 2 (86%) completed the evaluation of the didactic experience.

4.1 Usability Study.

A survey was applied among the 60 students to capture their perception about Portfolio's usability, adapted from the proposal in [1] designed to obtain a usability index of software applications. For classroom 1, the average obtained is 71.086, while for classroom 2, it is 74.553. Hence, both cases suggest that the Portfolio's usability is within the best acceptability range; i.e., students assess the tool as good according to the interpretation of the index in [1].

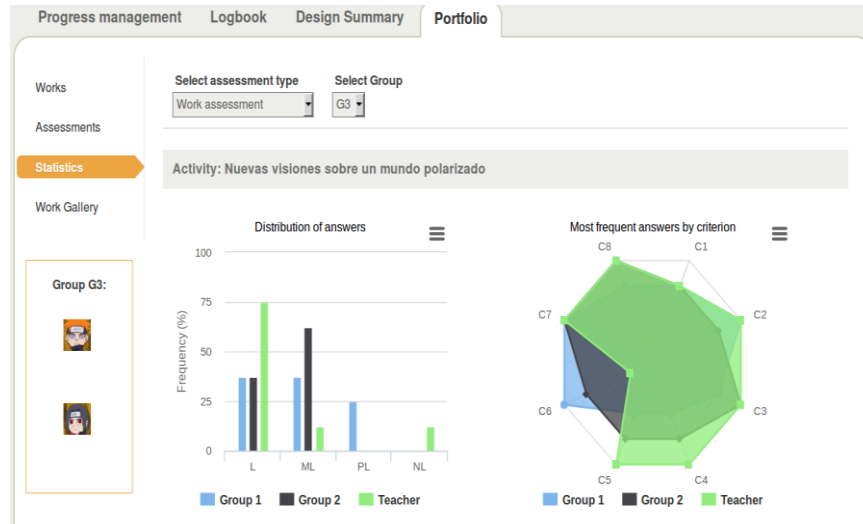


Fig. 2. Teacher view of Statistical Section which includes a menu of available filters, a results' graphic display area that identifies the activity, evaluation histogram (1) and radial chart (2).

4.2 Perception Survey about the Portfolio's Usefulness.

A qualitative analysis of the Portfolio was performed by means of a survey developed by the research team and applied to all the students during the pilot experience. The survey looked into the students' perception about the implications of the Portfolio on the learning and evaluation processes, and also of the tool's usefulness. The survey is organized in three parts. The first part focuses on the Works module; the second on the Evaluations module; and the third part contains questions about the Statistics and Gallery modules. The questions are statements that express a positive or negative valuation of the e-portfolio's functions. There are four levels of responses: strongly disagree (MD), slightly disagree (LD), slightly agree (LA) and strongly agree (MA). The neutral level was discarded to force an expression of positive or negative opinion. The results of the perception survey show that for all the positive statements regarding the usefulness of the Portfolio, most students either strongly or slightly agreed, with percentages above 70% between both options. Regarding the negative statements about the usefulness of the Portfolio, students' responses were more heterogeneous without a clear trend unlike the case of positive statements. The distribution of this survey's answers is shown in detail in the Appendix.

Fig. 3 shows the results of the survey questions that more directly address –in the opinion of students– the impacts of the Portfolio on the reflection about their learning process. Fig. 3(a) shows the results of a question that inquiries whether the evaluations performed made them reflect on their own learning process; student responses are somewhat heterogeneous, with an agreement of 50% for students in classroom 1 and 75% in classroom 2. Fig. 3(b) shows the results of a question referred to the val-

orization of the evaluations' graphic summaries in promoting reflections about teamwork. In this case, 82.5% of classroom 1 students strongly or slightly agreed, while this was true for 85.7% of classroom 2 students.

4.3 Discussion Groups

Two discussion focus groups were conducted made up by students from both classrooms in the pilot experience. The purpose of this activity is to understand the meanings attributed by students to their participation in the experience, considering the valorization of the e-portfolio as an environment to support the reflection and motivation of their learning processes. The classroom 1 group was formed by six students. This focus group suggests: i) Broad approval to the e-portfolio:

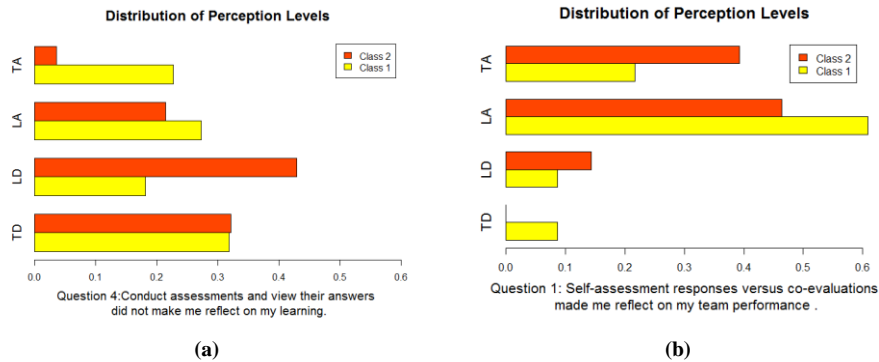


Fig. 3. Both classroom students' perceptions regarding the question about their reflection process in (a) the use of the Evaluations section and (b) the use of the Portfolio's Statistics section.

The main attributes mentioned are: ease of use; interaction with students from other schools; all works are available in the same place; and that it can be used both at school and home. ii) Group co-evaluation was a matter of debate as there was a lack of consensus on its proper use by classmates. Classroom 2 group was made up by five students. The following can be summarized from the conversation: i) All of them stated to like the portfolio, that it was something new and fun to use, ii) Most thought that the evaluations were easy to use and some said that they would like to add comments per criterion in addition to the achievement level. One student mentioned that this way, the teachers could also explain their evaluations.

5 Discussion and Conclusions.

The results of the usability study show that students qualified the e-portfolio in the acceptable category, with a usability index of 71.1 in classroom 1 and of 74.6 in classroom 2; both values are within the "good" usability range. This outcome is consistent

with the results collected with other evaluation tools, where students suggest several elements to improve the Portfolio's usability.

The results of the perception survey show that most students positively assess the Portfolio as a tool that supports work posting, comprehensive learning evaluation and the emergence of moments of reflection and awareness in the context of the didactic experience developed.

Discussion groups confirmed the outcomes of the prior surveys and complemented them by specifically arranging the critiques to the tool being proposed. One element worth highlighting is the diversity of perceptions around the co-evaluation process of the team's performance; while it was extremely well assessed by student from classroom 2 as a reflection driver for the development of teamwork, the students from classroom 1 considered it an uncomfortable and unfair process. On this regard, it should be mentioned that the two classrooms involved in the pilot experience are part of two different school situations which could probably explain such diverging opinions.

Based on the outcomes emerged, we can conclude that our e-portfolio meets the role of contributing to the awareness and reflection of students about their learning process, particularly concerning the development of teamwork skills, as well as in feedback processes of works posted in the platform. Another relevant aspect is the role of teachers in the design of didactic experiences, which in this case were directly related to the development of different evaluation guidelines which made it possible for such guidelines to be extremely well contextualized and therefore, to be perceived as easy to be developed by students. On the other hand, the Portfolio can also support teachers when monitoring the work of students, enabling them to compare their own perceptions of the work performed by students regarding the evaluations they get in the peer review.

Most of the findings or confirmations that the e-portfolio is useful to support the process of awareness and reflection of students are transferable to other learning communities and are related to the focus on a comprehensive assessment process, which not only emphasizes the products if not the underlying processes.

Future work is expected to complement the feedback provided to students and teachers with analytics of the activity in the portfolio of the participants of the didactic experience, such as those proposed in [15]. We will test these learning analytics in the Kelluwen platform with didactical designs concerning critical reading and citizenship.

A Appendix

Results of the Perception Survey on the Portfolio's Usefulness

Questions	Frequencies			
	TD	LD	LA	TA
T1. It was hard for me to post works.	11	6	14	19
T2. It was easy to access posted works.	13	9	18	11
T3. It is easy to find the works of my group	14	6	10	11
T4. I was able to identify the work that was going to be evaluated by other groups.	4	10	25	12

Questions	Frequencies			
	TD	LD	LA	TA
T5. It was useful for my group to be able to see the works posted in the Portfolio.	5	16	15	14
E1. Knowing the evaluation guidelines beforehand was useful to better understand my expected learning.	9	1	27	14
E2. Knowing the work evaluation guidelines before was useful to improve my work.	5	11	23	11
E3. The Portfolio shows clearly which activities are to be submitted to evaluations.	8	8	21	14
E4. Performing evaluations and seeing their answers did not make me reflect about my learning.	8	12	17	14
E5. I didn't like performing digital evaluations.	6	14	15	16
E6. Co-evaluations helped our groups to improve their collaborative work.	7	8	22	14
E7. The results of the evaluations helped me learn about which objectives were achieved and which weren't.	10	8	15	17
E8. I was unable to see the works of other groups during the evaluation.	6	10	21	14
E9. It was easy to evaluate other groups.	12	14	14	11
E10. Interacting with other groups during evaluation was useful to improve our work.	7	10	23	10
R1. Self-evaluation answers versus co-evaluation answers made me reflect about my teamwork performance.	6	10	19	15
R2. I was unable to compare how other groups and the teacher evaluated me.	10	7	21	13
R3. I was able to better understand the performance of my work group by looking at the charts in the Portfolio.	8	11	16	16
R4. I think it is a good idea for the Portfolio to include charts to be able to see the answers of the evaluations.	10	9	16	16
R5. I think charts make it difficult for me to understand evaluations.	5	14	18	14
R6. The information in the radial chart was useful for me.	9	7	19	16
R7. Being able to see works of other groups in Portfolio was useful for my learning.	7	13	20	11
R8. Being able to see other works in the Gallery was useful to guide our own work.	3	8	24	16

Acknowledgments

This research was supported by DID-UACH and FONDECYT under Grant no. 1150545 "Redes Sociales y Medios de Comunicación: Modelo de análisis basado en minería de datos para la comprensión del ecosistema informativo chileno en internet y la educocomunicación ciudadana en la red".

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Are you thinking what I'm thinking? Representing Metacognition with Question-based Dialogue

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Abstract. In the following paper, we present *Noracle*, a tool for creating representational artefacts of metacognitive thinking in a collaborative, social environment. The tool uses only question-asking, rather than the typical question/answer paradigm found in threaded discussions, as a mechanism for supporting awareness and reflection on metacognitive activity, and for supporting self-regulated learning. The web-like artefact produced by learner contributions is intended to support learners in mapping a given domain, identifying points of convergence and recognizing gaps in the knowledge representation. In this paper, the authors present the model of the tool, a use-case scenario and a discussion of the opportunities and limitations related to this approach.

Keywords: self-regulated learning, reflection, metacognition, learning analytics, inquiry, knowledge representation, technology-enhanced learning

1 Introduction

The basic metacognitive element of awareness and reflection is *self-observation*. Meaningful self-observation affords the opportunity for judgement and reaction, providing evidence of the impact of certain strategies, beliefs and attitudes toward one's learning [23]. It also requires strong inquiry skills, to ask basic questions like "*what should I observe and how do I best observe it?*" toward interpretative questions such as "*why is what I am observing happening and how do I control it?*" Self-observation seems deceptively easy. If not trained and supported, it can be too superficial or unstructured to give the individual much insight (*ibid*). In addition, though Self-Regulated Learning *requires* reflection on learning to learn, it is typically perceived as a more solitary activity occurring outside of the classroom [3].

To support learners in acquiring learning strategy knowledge, we believe it is necessary to provide tools that allow for 1) *social* integration of knowledge and experience about learning, 2) a *structured* space to explore and represent knowledge, as well as identify relevant knowledge gaps, and 3) opportunities for *reflection* and exchange on how best to address knowledge gaps. In this paper, we present a model

of a social, structured space for both reflecting on metacognitive assumptions and representing metacognitive knowledge, using question-based dialogue. We illustrate the application of this model at these early stages using a tool called LiteMap [5], and discuss the possibilities and limitations involved.

Our model, which we refer to as *Noracle*, is primarily based on the *construction-integration* theory of knowledge acquisition. New knowledge is integrated into an individual's *conceptual map* through reflection, by anchoring it to existing information [17]. In the context of Technology-Enhanced Learning, we apply this model to collecting and integrating *strategy knowledge*, or *metacognition*, among a group of online learners to create a virtual, visual map of inquiries related to their metacognitive thinking. Through use of questions, rather than answers, we draw on the traditions of Problem-Based Learning (PBL) and Inquiry-Based Learning (IBL) to encourage deep-level reasoning and support the integration of both cognitive and metacognitive strategies in learning to learn [8][11]. *Noracle* is intended to build upon this tradition, triggering and exploiting human curiosity to support awareness and reflection. The shared visualization of inquiry that is born through collaboration in this space is the mechanism by which metacognitive thinking is explicitly *represented*, which might not only be “uniquely human”, but also the building block of contextual knowledge construction [18].

2 Background and Related Work

Inquiry is the cornerstone of all learning. In the next paragraphs, we discuss how structuring inquiry in a social learning setting can contribute to helping learners become more aware of how they learn.

Constructivist theory suggests that learners can become more skilled at recognising certain opportunities and challenges to their learning over time, regulating their thoughts, emotions, behaviours and learning contexts appropriately [12][24]. These skills are collectively referred to as *Self-Regulated Learning* [15][23] and have become a central goal of contemporary education [19][20]. However, self-regulation is a *process* and learners require scaffolding to break through certain challenges. It is necessary to utilise the social environment of learning to support learners' self-regulation by exposing them to new perspectives, ideas and methods through their peers and tutors. In this way, we assert that all self-regulation in learning is mediated and influenced by what is called *Socially-Shared Regulated Learning* [10]. Social components help to *scaffold* the process of learning to self-regulate also by *representing and interrogating* knowledge within a group. Boud suggested that all learning originates from the curiosity and motivation of the learner [2]. Problem-Based Learning, Inquiry-Based Learning, and Collaborative Learning attempt to trigger this process by providing open, partial pictures of a problem and relying on students' collaboration and reasoning to engage students in mapping out the problem area [7][11][17].

Social Learning approaches necessitate *quality* learner participation. Research indicates that learners are generally unskilled in asking deep questions that result in

high-order thinking processes, such as meaningful reflection [8][9]. Learners also appear to have difficulty in *distilling* answers and engaging in cognitive *monitoring* [1]. Developing strong skills in question-asking and problem-mapping are, therefore, important precursors to success in reflection on learning. Skills can be strengthened by association with more highly skilled peers or with a tutor through facilitated practice [4][8]. Spending a greater portion of time considering learning strategies and the various implications these strategies have for performance is already a part of both PBL and IBL [3][11]. However, similar to the acquisition of content knowledge, the representation of that knowledge is important. Learners need a way of structuring their *strategy knowledge*, as well as their *self-knowledge*, to be able to recognize and fill in gaps related to how they learn. Noracle is an opportunity to mobilize technology as both a tool to encourage and represent inquiry.

3 The Noracle Model

In this section we present the main entities of Noracle and discuss their role and interconnection. Figure 2 illustrates these entities, identified as Classes and Relationships. *Learner* is a class that is used to describe the ordinary participants of Noracle. Apart from a standard set of attributes used to identify them (i.e. username, email, password), learners are the main agents that interact in the Noracle Space through various actions, discussed below. A *Question* is the central Class of Noracle spaces. Fundamentally, a Question is defined as a free-text field, which is authored by a Learner. Moreover, a Question can be *linked* to other Questions so as to form the web of Questions described below. Once a Question is posed, linking it to other Questions is optional. A Question linked to another Question joins the space of the pre-specified Noracle Space whereas a Question that is not linked forms a new Space.

Learners can provide feedback on Questions through *Annotations* and *Ratings*. These two entities share the same goal, which is to provide a mechanism for assessing the usefulness and the quality of a Question. An *Annotation* is created using a free-text field and multiple Annotations by an arbitrary number of Learners can be attached on a Question. For using Noracle in the context of Socially-Shared Regulated Learning, Annotations can be derived from the research literature on Self-Regulated Learning to indicate whether or not a specific question relates to how the Learner is thinking, feeling, or behaving, or the context in which learning occurs [15]. An optional, single *Rating* is provided by each Learner following a Likert rating scale.

A *Moderator* is a special type of user who has the permission to make modifications on the content created in Noracle. The purpose of this user is to be able to supervise the formation of a Noracle Space and its contents and make sure it doesn't deviate from the Noracle objectives and context.

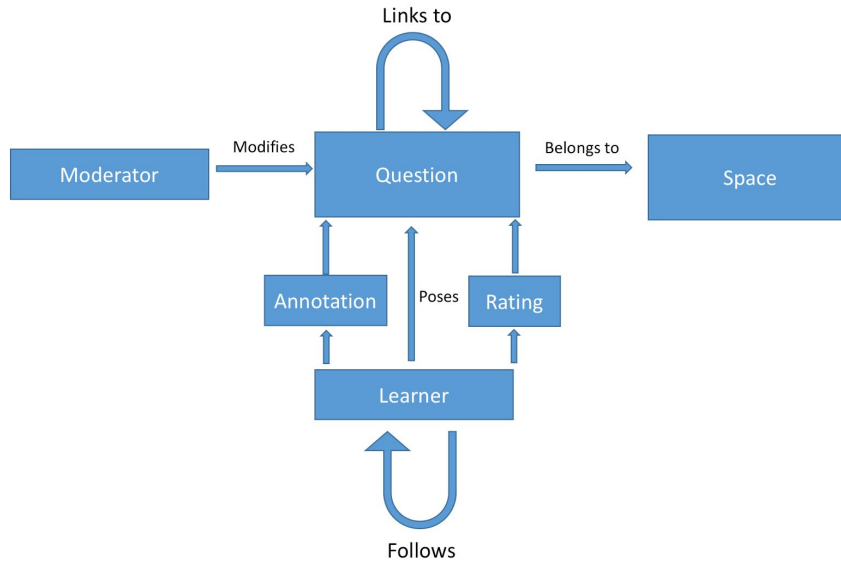


Figure 2: The Noracle Model

4 Applying Noracle for Metacognitive Representation

To illustrate the concept of Noracle without a functional prototype, we decided to appropriate a tool for structuring argumentation called LiteMap [5], in which we bound a small selection of 5 colleagues to deploy only the tools that are representative of the entities described in the model above to explore challenges in learning to learn. This included creating a user profile, raising an “Issue” as a Question, providing an Annotation in the comments, responding with Questions to the Questions of other Learners, using the “thumbs up/thumbs down” feature as a Rating and exploring the visualisations of social and issue networks as Space. For the moment, the directional arrows were ignored, except to illustrate that a connection between two Questions had been established (see Figure 3). The artefact created is public on LiteMap as “Noracle Test 1.” While LiteMap is not a perfect representation, we conducted this exercise to highlight the basic components of the model and the underpinning pedagogical theories of Noracle.

Noracle intends to *train* question-asking by demanding that Learners engage only in question-based *dialogue* under supervision and facilitation (of a Moderator, for example). The starting *nodes* or Questions that Learners ask are triggered by their individual curiosity and then expounded upon through the addition of *follow-up* questions (submitted by any user) that help the original asker to expand or narrow their focus on a particular issue. As the nodes become linked, a web of Questions emerges that represents the metacognitive reflections of the individuals involved (see Figure 3). As the web expands, Learners and Moderators can gain insight into what

the cohort does and does not understand about learning to learn, uncovering gaps in learner knowledge that can be actioned by an educator (possibly the Moderator).

Through the Rating feature, the Learner can begin to create their own *peer-learning* networks by following those users who have proposed the most highly-rated Questions. The Moderator can also review highly-rated questions with Learners as part of the classroom content, to improve the quality of their question-asking by distilling features of useful questions. Additionally, the Moderator can use this data to improve awareness for the *social learning dynamics* of the cohort.

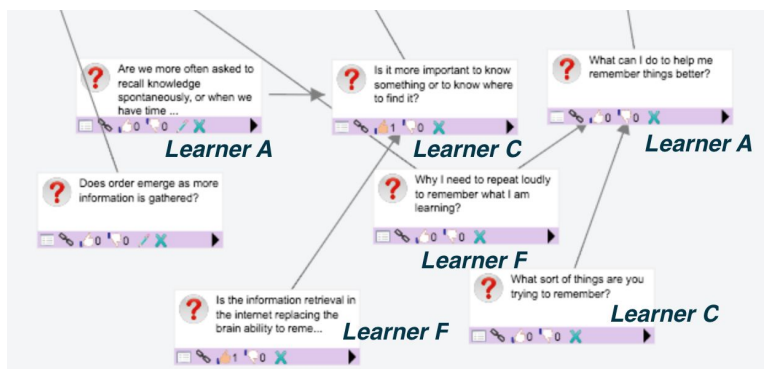


Figure 3: Question Web in Noracle

The Annotation feature gives Learners and Moderators additional information about what *type* of Question is being asked (whether it relates to thinking, feeling, behaving or context), to understand where specific challenges might lie. If a particular Learner consistently asks questions related to a particular area of self-regulation, for example, this gives Learners and Moderator an indication of the Learner's interests and which skills that Learner needs to build, to inform appropriate interventions.

The Annotation feature and visual representation also trigger reflection in other ways. Suthers discussed this phenomenon in terms of "*missing units*" triggering search [21]. Introduction of a *gap* (i.e. an Annotation field that prompts the user to think about what kind of question they are asking) encourages learners to consider how that gap can be filled. In fact, the existence of only Questions in the space has its own reflexive value in the absence of an Answer entity.

5 Discussion

Noracle as an information system is still at its early development stages and does not have robust evaluation results at this time. However, we can gain insights about its effectiveness from the research literature and anecdotal evidence from application of the model in the physical classroom, as well as the informal LiteMap trial. Noracle was developed in 2012 by Track2 Facilitation (<http://www.track2facilitation.com/>) as a face-to-face reflection method (similar to "speed-dating" with questions) in the

context of non-formal learning. Participants have consistently described this method as being helpful to their process of deliberation and sense of self-esteem in course evaluations. Experiences with the method tended to confirm prior research findings that absence of answers leads to *self-discovery*, which is a more satisfying experience for learners [13]. With facilitation by a moderator, the effects of self-discovery on learning outcomes are even more pronounced [14].

The decision to digitise this tool emerged from the recognition that not all learners were able to organise and represent what they took away from the experience of Noracle. They had difficulty remembering who had given them a useful follow-up question in the group, for example, and it was difficult to create a *joint representation* of complex topics with the limitations of physical space. The "enhancement" that technology can offer this tool is exactly regarding *scale* and *analytics* [8]. The LiteMap trial indicated that Noracle can be used among an open group of anonymous, distributed learners, or a closed cohort of students, for example. It can create representational artefacts that are more considerable and complex than those that would likely be attempted in a physical classroom, and it can operate in both synchronous and asynchronous learning environments. Moreover, it can collect data on users, their contributions and their connections to one another over time.

Representational maps have been shown to resolve some of the issues of "coherence and convergence" found in typical classroom forums, and they promote the generation of hypotheses and collaborative activity [22]. This addresses, at least in part, the issue of *motivating* learners to ask questions, so that they can become skilled at other aspects of inquiry [9]. The analytics collected through Noracle can be used in real time and over time to deliver insights that impact both teaching and learning, especially in conjunction with a representational artefact. For example, research indicates that peer-learning in the context of a developmental construct, such as learning to learn, is more effective than individual study [6]. Being able to estimate the prior knowledge of a peer-learner has also been shown to produce more positive impacts learning outcomes [16].

However, Suthers [21] cautioned that representations have their own impacts on collaborative and individual inquiry. Surely the presence of this artefact limits the types of discussions that can be had about learning, simply because the tools that are there to help learners express themselves are limited. Not only do the elements described in the model limit what can be known from inside of Noracle, but Learners will additionally produce their own limitations, based on their own perceptions of the system.

6 Conclusion

Though strategy knowledge is as important as content knowledge in learning, learners (and teachers) tend to spend much more *social*, *structured* time on the perceived primary task of learning content knowledge and less on the perceived secondary task of reflection and learning to learn. As a result, many learners are much more aware of

what they know than *why* they know it, which frustrates the *transfer* of learning skills from one domain to the next. By scaffolding inquiry in a tool such as Noracle, we believe that learners can both gain access to new ideas and perspectives on their learning strategies, and hone their skills in question asking, while contributing to the representational artefact of metacognitive knowledge created by the group. Over time, patterns emerge that we believe can provide the learner with insight and give them a foundation upon which to change or support their current approaches. In the future, we hope to fully implement this tool, accompanied with preparatory and debriefing activities that a Moderator can use to facilitate its use. We also intend to conduct a robust evaluation of the tool and its effects on learner motivation, metacognitive awareness and general learning outcomes.

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Considering Self-Efficacy in Reflection

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Abstract: There is a relationship between self-efficacy and the process of reflective learning. How they may influence each other can be explored by considering the steps in a reflective learning cycle. For each step, there are ways self-efficacy may be affected by how reflection is conducted, or may impact on how reflection should be conducted and supported. The paper outlines such connections, thus providing a starting point for further research on how to take self-efficacy into account when planning and designing for reflective learning and needed tool support for this.

1 Introduction

What are the consequences for learning and performance if Annie, a student of engineering, perceives her abilities in maths to be weak, sees tests as towering hurdles, bad results reflecting her lack of skills and good results surely being due to pure luck? What if Ethan the engineer perceives his good-but-not-excellent skills to be way above average, seeing little need to prepare much for challenging work tasks and considering whatever goes wrong as due to circumstances? What happens when these people reflect on their achievements? Should the initiation and guidance of reflective learning take such characteristics of the learner and work settings into account? We think yes. To argue for this, we need to take a step back and look further into the connection between reflective learning and Self-Efficacy (to be abbreviated as S-E).

Reflective learning can be considered as a *conscious re-evaluation of experience for the purpose of guiding future behavior*, with attention to feelings, ideas and behavior [1]. Reflection is regarded as essential for learning [2], [3]. In what follows, we use the term “reflection” and “reflective learning” interchangeably. Reflection can be individual, or it can be collective [4], involving the articulation and sharing of experiences and collaborative construction of knowledge (e.g. [5]). Reflection takes place in the workplace as well as in educational settings. We will in this paper refer to the activity reflected upon as “work”, whether it refers to the everyday work of an employee or the learning activities undertaken by a student.

A factor that plays an important role in how the individual performs in her work (e.g. how tasks are viewed, whether they are taken on, how they are conducted, whether they are completed) is the *perceived S-E* of the person with regard to the various tasks. (We will from here on refer to “S-E”, taking as implicit that it is as perceived by the individual). S-E is a construct originating in the social cognitive theory of Bandura [6]. S-E addresses the individual’s belief in their ability to succeed with a task and relates this to the individual’s experiences and interaction with others. e.g. learning from people who serve as role models. S-E may affect the choice about whether to engage in a task and whether to complete it. In the context of reflective learning, S-E thus plays a role in determining what kind of experience is generated

and how the individual further acts upon it. This points to S-E as relevant to those who wish to provide adequate support for reflective learning [7], including educators working with student-active approaches to learning (for instance self-directed learning [8] or problem based learning [9]) and to those developing tools supporting these activities.

Existing theory of reflection (e.g. [10]) and research addressing practical support for reflection in pedagogical contexts (e.g. [11], [12]) already relates to issues that form key elements of socio-cognitive theory. What we aim to do in this work-in-progress-paper is to systematically consider S-E in context of a reflective learning cycle, thus providing some anchor points for support (technological or other) for the reflective learner. It is important to stress that while this paper has a focus on the connection between reflection and S-E, the ultimate objective for continued research is to unveil ways in which adaptation and support (through technology or otherwise) may be introduced to improve the reflective learning process.

In the Background section, we provide a brief outline of the concept of S-E as well as a cyclic model of reflective learning (the CSRL model [7]). In section 3 we proceed to discuss how S-E potentially *impacts on* the steps and transitions in the reflective learning cycle. In section 4 we consider how S-E may *be affected by* steps in the reflection cycle. Section 5 concludes the paper with a discussion of issues to be addressed in further research along this vein, including some limitations and challenges.

2 Background

We here outline existing research on self-efficacy and the reflective learning process.

2.1 Self-Efficacy

At the core of the social cognitive theory [6] is the understanding that humans are agents deliberately using their actions to influence their own functioning and their surroundings. Influential factors in the self-regulation of human motivation and behaviour include not only S-E but also goal systems, outcome expectations, perceived environmental facilitators and enablers, and environmental impediments [13].

There are four main sources of S-E: mastery experience, social modelling (learning from role models), social persuasion, and physical and emotional states [14]. Mastery experience is regarded as the most significant among these. S-E can be measured with instruments adapted to the specific domain [19]. To get a measure of S-E, the individual is typically asked to rate a set of statements about their confidence (e.g. on a scale from 0% to 100%) that they will be able to perform the type of tasks in question. By measuring S-E, it is possible to compare within and across individuals how S-E develops over time and/or differs in a population.

According to Schwarzer and McAuley, the usefulness of S-E as an ‘operative construct’ relating to the self lies in its three components: competence (how behaviour is attributed internally), the temporal perspective (how future action is predicted) and behaviour (as opposed to attitudes or personal characteristics) [15].

An important point here is that S-E is not *fixed* – it develops over time as a consequence of the person's actions/experience as well as changing circumstances and requirements. Also, the relative importance of different areas of S-E for a person might vary over time (e.g. due to changes in roles/responsibilities). Thus, in measuring a person's S-E, we should not consider it as a trait revealed once-and-for-all, but rather as a measurable factor that can be used to gauge the current situation and that can be influenced by providing the right means. Thus self-efficacy might both vary over time and across different domains of knowledge.

There exists a significant body of empirical research establishing connections between S-E and other parameters of human behaviour such as performance. Generally, S-E has been found to influence performance in a positive way. Some studies have however found that increased S-E may have *adverse* effects on performance (for instance leading the individual to assume that less preparation is necessary to succeed with a task) [16]. Tierny and Farmer argue that the negative effect of high S-E on performance may be a characteristic of controlled laboratory settings, as opposed to more complex, real-life settings for which the threshold for a positive impact of S-E is higher [18]. Tierny and Farmer, for instance, conducted a longitudinal field study of creative S-E in a workplace, finding that by enhancing creative S-E, creative performance was also improved. Bandura, responding to studies showing null or negative effect of S-E on performance (e.g. [16]) points out that S-E is *one* factor within social cognitive theory and needs to be considered in context of the rest [13].

All in all, the body of research supporting a potentially positive influence of S-E on performance is substantial enough for us to make the basic assumption that increased S-E – or, sometimes, a more realistic S-E, may be favourable to performance.

Finally, it should be mentioned that we may talk about the *collective* efficacy of a group, which is bigger the more interdependent effort is required when a group undertakes a collective task [17]. Collective efficacy has relevance in the present context as both work and reflection may be collaborative.

2.2 The Reflective Learning Cycle

The process of reflective learning can be represented as a learning cycle as in the CSRL model of reflective learning [7]. The reflective learning as it evolves over time (e.g. in a workplace) can be considered as a set of interconnected reflection cycles, often involving more than one level in the organization. A key point of the CSRL model is that the steps of the reflective learning cycle may be supported by tools, which means the model can serve as a guide to the design and/or selection of appropriate technology to aid reflective learning. In this paper, we focus on the four main steps of the cycle and the transitions between them, considering implications for tool use as further work and as a main purpose of this work-in-progress.

The main steps of the CSRL model (see also Figure 1) are: Do and plan work – the activity in which experience is being generated; Initiate reflection – a spontaneous or planned, unstructured or systematic initiation of reflection based on data (formalized or not) about the work experience, resulting in a frame for the reflection (participants, resources, scope, objectives...); Conduct reflection session – engage in activities such as reconstructing experience, possibly sharing it with others, clarifying its meaning

(e.g. what are current challenges), finding solutions and creating an outcome; Apply outcome – implement the result of reflection as a tangible change to work or a changed readiness for action, or possibly initiate another round of reflection.

3 Considering the Impact of S-E on Reflection

A key point in this paper is that S-E plays a role in how reflective learning unfolds. We tentatively propose some ways in which transitions in the reflective learning cycle may be influenced by the S-E of the learner (summarized in Fig. 1):

Plan and do work – As described above, S-E influences performance, in particular decisions on what to do and how. It influences the shaping of the experience following from interpreting emotional reactions and from attending to aspects of the situation considered to be relevant, important and (maybe) within the learner's power of influence. S-E may also influence which data becomes available for reflection. The collective efficacy of a group working together may also be influencing on work activity and experience.

Initiate reflection - S-E influences what is perceived as a (reflection-triggering) discrepancy and what is worthwhile reflecting on (e.g. because it is within the learner's power of influence). This means there may also be an influence of S-E on the frame for reflection created at this stage: What is the scope, what are the relevant issues/constraints to consider, what are realistic objectives/types of outcomes, whom is it relevant/viable to involve (for co-reflection) etc.

Conduct reflection session – Again, considerations about what are possible solutions and viable options for bringing about change will be influenced by the individual's belief in her power to influence events. Also, especially in collaborative reflection, social learning mechanisms may play a part in determining who learns what from whom in the group. It is likely that participants will learn more from the experience shared by those considered similar to themselves (role models). Furthermore, considering the reflection session as an experience (in line with the work experience), S-E will impact on how this experience – of mastering an activity/process and contributing to its results – is shaped. If reflection is conducted in a group, the collective S-E of the group with respect to reflection as well as other collaborative work activity may impact on the reflection session. Participant's self-efficacy can influence the extent to which he or she contributes to the discussion.

Apply outcome – S-E may influence on the learner's decision to implement a change, as this may be a question of confidence that it will work out. Similar considerations apply to the decision to involve others. (Do I dare? Will it lead to anything?)

One issue in considering the impact of S-E in this process is whether attempts are made to *measure* the S-E and somehow use it to aid the process. In this case, a whole range of challenges arise along with the possibilities for useful insight. One question – on which we will not elaborate here – is the reliability and validity of measurement: is it S-E, and in the relevant area, that is being measured, and is the measurement reasonably accurate? Existing research (e.g. [19]) indicates that this can be adequately solved. Another question pertains to when measurement is being made, and whether it

is repeated (e.g. in a before-after research design). Furthermore, knowledge about the S-E of an individual may be available to the person, but also be made available to others, e.g. a manager, a teacher, peers, or some organizational intelligence system.

Knowledge about S-E in combination with other knowledge about the situation/activity could be used to aid decision on when it is useful/appropriate to reflect, with whom to reflect, and how (e.g. which questions might be addressed, which data should be available, which outcomes/types of outcomes to aim for, what to do with them...). As an example, it may be beneficial to individuals who are low on S-E to be paired with role models, both in work and in reflection sessions, to benefit from observational learning and vicarious experience.

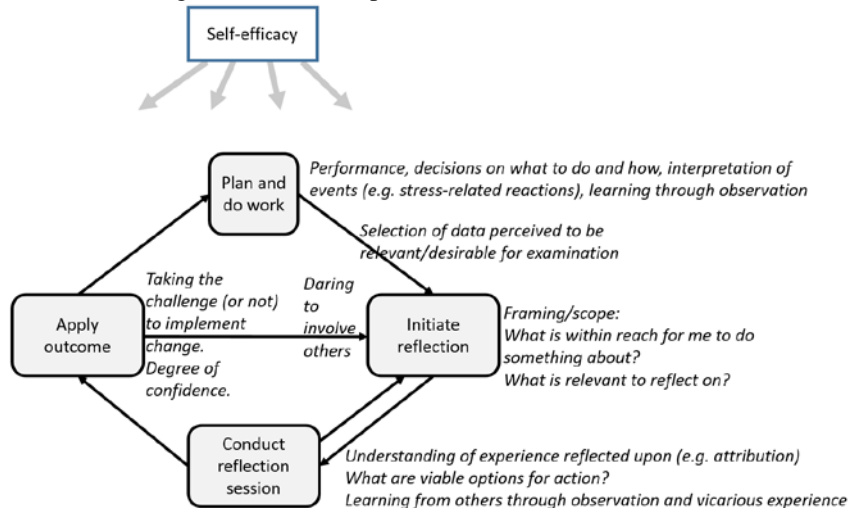


Fig. 1. Potential influence of S-E on the reflective learning cycle

4 Considering the Impact on S-E of Reflection

In looking for aspects of reflective learning influencing S-E, we may look for points in the reflective learning cycle likely to be influenced by mastery experience, learning from role models, social persuasion and interpretation of one's own emotional reactions. Each of these factors could in principle be relevant anywhere throughout the cycle through the *experience of reflective learning*. In particular, we should make sure to consider both the work experiences reflected upon and the experience of engaging in (and mastering) the process of reflection.

Ideally, the reflective learning process should build and strengthen the understanding that it is possible to reach insight about one's situation and do something about it.

We briefly indicate some ways each of the steps in the reflective learning cycle may impact on S-E:

Plan and do work – S-E may be influenced through mastery of work tasks, observational learning and social persuasion. This may also include collective efficacy.

Initiate reflection – S-E may be influenced through the experience of taking action to do something about issues at stake, possibly also by involving others.

Conduct reflection session – S-E can be affected by learning through vicarious work experience shared by role models, social persuasion, mastery of the reflection activity itself (conducting the session, seeing it resulting in outcomes), the use of insight on S-E (as measured and/or experienced) to identify action that will improve mastery. These points may apply also to collective efficacy.

Apply outcome – S-E can benefit (or suffer) from the experience of being able (or unable) to bring about change.

5 Discussion

We have given an outline of ways in which S-E may influence, and be influenced by, steps in the reflective learning process. Our intention with this paper is to argue for the potential of pursuing these connections in more detail through further research. Can the reflective learning cycle, appropriately supported, effectuate a virtuous cycle of increased S-E and increased work and/or learning performance? This question holds potential for being empirically explored as part of investigating actual reflective learning processes, for instance in a workplace or in a course in higher education.

We propose an agenda for further research along the following lines:

- Generally explore in more depth theoretically and empirically how S-E, as a measurable characteristic of a person in context of particular situations and tasks, can be taken into account in a way that aids the reflective learning process. This could mean tailoring the process to the individual, but also to consider the composition of teams (i.e. with regard to social learning) and collective efficacy.
- Apply research designs in which S-E is measured before and after a pedagogical intervention (e.g. introduction of a particular type of activity promoting active/reflective learning, and/or the use of technology support for reflection) to explore the possible impact on S-E. The connection between change in S-E and change in performance can also be explored, if relevant.
- Explore the effect of making S-E (measured or otherwise inferred) a topic of reflection, individually or through discussion with others. Questions in an S-E scale may serve the simultaneous purpose as trigger and guidance of reflection.
- Use current insights on technology support for reflection (e.g. from the MIRROR project [7]) to see how the above can be aided by computerized tools. In addition to building upon work in the TEL area, insight from Learning Analytics (LA) such as [20] might also be beneficial here.

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